STEP Project – Work Package 1

ERANET Cross-border Joint Research Programme

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STEP Project – Work Package 1
State-of-the-Art: Review of Best Practice

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Content

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State-of-the-Art: Review of Best Practice

Report for Work Package 1 - State of the Art Review of Best Practice, for STEP - Short Term Prediction project

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1 State-of-the-Art Best Practice

1.1 Introduction

The aim of this document is three-fold. First, it provides a state-of-the-art overview of the core elements in short-term forecasting systems. In doing so, we discuss short-term forecasting systems and their constituent elements, decision support systems and traffic control algorithms, as well as some open issues.

Second, it reviews multiple applications of short-term prediction systems in Europe. It is worth noticing that since many of these applications are still undergoing some testing, there was no much information available to the public. Nevertheless, the cases presented here provide a general overview of the trends in Europe regarding the application of short-term algorithms by Traffic Management Centres and other government agencies. Table 1 shows a summary of all the cases reviewed as part of the project.

Third, it provides some conclusions on the topic of short term prediction algorithms and its applications in Europe, as wells as some recommendations both for practice and future research.

Table 1 Summary of Reviewed Applications

City / Country	Type of network	Time line	Software	Objective
Berlin / Germany	Urban network	Currently operational	VISUM Online	To provide information
Dusseldorf / Germany	Urban network	Currently operational	PTV Traffic Platform	To provide information and control strategies
Helsinki / Finland	Motorway	2005	SOM neural network	To provide information
London / United Kingdom	Urban network	Currently in testing phase	OPTIMA	To provide information and control strategies
Naples / Italy	Motorway	Currently operational	RENAISSANCE	To provide information, and to detect incidents
North Rhine-Westphalia / Germany	Motorway	Currently operational	OLSIM	To provide information
Rome / Italy	Motorway	2008	Pattern Matching and Artificial Neural Networks algorithms	To provide information

The remainder of this document is organized as follows:

- Section 2 provides a state-of-the-art review of short-term forecasting models, which is a core element of many decision support systems and control approaches, discussed in section 3 and 4 respectively.
- In section 5, we discuss some ‘open issues’ which are deemed important when applying short-term prediction to real-life cases.
- Section 6 reviews the applications mentioned in Table 1.
- Section 7 summarizes the findings of this Work Package and our main recommendations.

2 Short-Term Traffic Prediction Models

2.1 Introduction

In the international literature a vast amount of studies has been focusing on short term traffic prediction, where short-term usually reflects a prediction horizon of up to one or two hours. In this chapter we provide an overview of different approaches to short-term traffic prediction. This elaboration has been drafted largely from van Hinsbergen et al. (2007), complemented with parts of Tampère et al. (2009). For more details or scientific references, the reader is referred to these two articles.

Prediction models can be subdivided into three main categories: naïve methods, parametric models and non-parametric models, and further subdivided after that (see Figure 1).

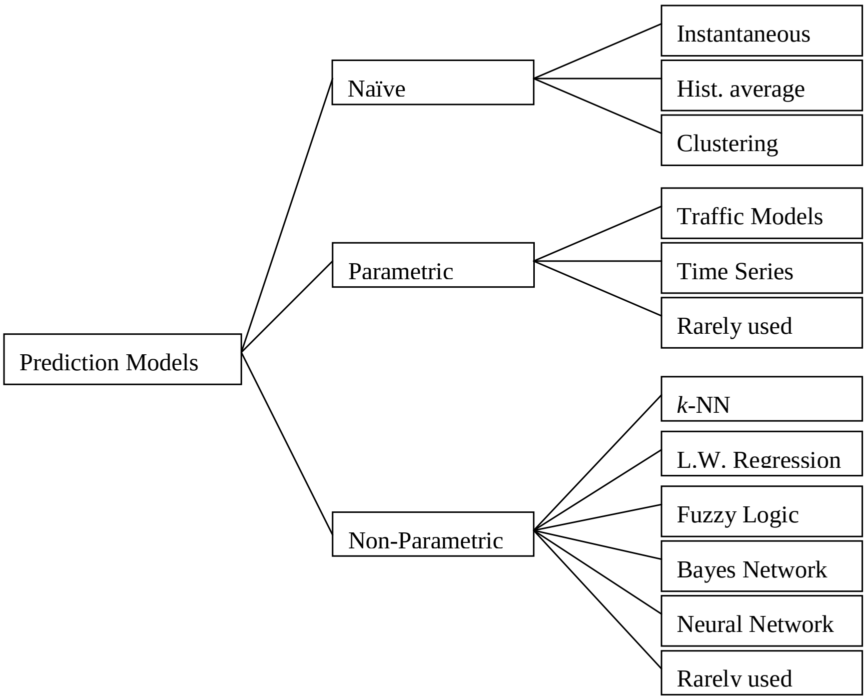

Figure 1 Taxonomy of prediction models (van Hinsbergen…)

Following the above categorization, the different types of prediction models are discussed in the following subsections.

2.2 Naive methods

The term 'naïve' is rather subjective, but can be interpreted as 'without any model assumption'. Naïve methods are widely applied in practice because of their low computational effort and easy implementation. The accuracy however is usually very low. Generally any parametric or non-parametric method was found to have a higher accuracy than these methods.

2.2.1 Instantaneous

When Instantaneous Travel Times (ITTs) are used as ‘predictor’, it is assumed that traffic will remain constant indefinitely (see e.g. the comparative article of Huisken & van Berkum, 2003). Although this method is very fast, as no calculation at all is required, its predictive performance is very bad because traffic is far from constant.

2.2.2 Historical averages

Averaging past traffic data will produce the historical average of a certain traffic variable (e.g. Rilett & Park, 2001 and Wu et al., 2004). Compared to more advanced techniques the historical average never comes out best, although sometimes it can outperform some prediction techniques on longer horizons. Sometimes, the historical averages are divided into time bins to improve performance (Hobeika & Kim, 1994).

Combinations of instantaneous and historical average all combine the last known measurement and the historical average in some way. These methods do not have high prediction accuracy.

2.2.3 Clustering

Clustering methods average traffic variables within a specific group of days based on similar traffic patterns. Applied algorithms are for example the Small Large Ratio and Ward’s Clustering (e.g. Chung, 2003). Sometimes, clustering is used for pre-processing input data (Chrobok et al., 2004). These clustering techniques have been shown to outperform historical average and in one occasion a linear regression, but are crude and therefore not often used.

2.3 Parametric models

The term ‘parametric’ indicates that only the parameters of the model need to be found using data; the structure of the model is predetermined. Knowledge on the traffic processes can be implemented in these structures, especially in traffic simulation models, which can aid in understanding traffic processes. Also, unforeseen cases such as incidents can be modeled. This is very useful for DTM purposes. Another advantage of these methods is that usually less data is needed compared to non-parametric models. Some parametric models have shown good performance, in accuracy as well as computational effort.

2.3.1 Traffic simulation models

There are two main classes of online traffic state estimation and prediction models for traffic networks: online full dynamic traffic assignment (DTA) models, and online traffic flow models. The former explicitly model demand, route choice and flow propagation through the network, whereas the latter only simulate flow propagation, while treating time-dependent demand and route choice implicitly as dynamic parameters or boundary conditions.

The principal achievements in online full DTA models are due to Mahmassani et al. (2001) and Ben-Akiva et al. (2001). They developed respectively the Dynasmart-X and DynaMIT models after the US Federal Highway Administration (FHWA) recognized the need to accelerate the development and deployment of DTA models and initiated the traffic estimation and prediction (TrEP) program in 1994.

An inherent problem with online full DTA models is the fact that for online calibration of the three sub models (demand, route choice, and supply), only one set of real-time measurements is available. The system is therefore highly underdetermined, potentially leading to calibration problems (e.g. Brandriss, 2001). A typical remedy is to give relatively high weights to prior estimates (offline calibrated) of the variables. This has the advantage of the model predictions converging smoothly to historic average traffic conditions as prediction horizon becomes longer. On the other hand, the flexibility of the model to adapt to the actual traffic situation is limited. An alternative remedy is to use real-time information to adapt only a subset of the variables, for instance those of the demand model, and to consider the actual settings of the other sub models as correct. This is largely the approach followed in the heuristic commercial model Visum-online (PTV, 2001). Also the more recent online DTA model of Flötteröd et al. (2008) adopts this approach, albeit different from the other online DTA models, in that it uses aggregate detector measurements for calibrating a disaggregate rather than an aggregate demand model.

Online traffic flow models are the alternative to the DTA-based approach. Here, real-time data is used for calibrating only the state variables of the flow propagation model, so that demand and route choice do not require separate sub models but can be implicitly treated as (dynamically varying) boundary conditions and parameters (split fractions at nodes). As such, the traffic state can be more flexibly adapted to the current traffic conditions. Various methods for online calibration of the online model were proposed, like heuristic approaches applied to microscopic (Kaumann et al., 2001) and macroscopic flow models (Muñoz et al., 2003) and fuzzy logic (Kim, 2002). However, most contributions in literature apply some form of Bayesian recursive filtering1 with a macroscopic representation of traffic dynamics.

Both first order traffic flow models, usually in the numerically discretized form of the Cell Transmission Model (CTM, Daganzo, 1994; Lebacque, 1996) – see for instance Kurzhanskiy & Varaiya (2012), who consider demand and supply uncertainty in the predictions, for an interesting recent application -, and higher order traffic flow models are used. The latter models, numerical versions of the model of Payne (1974) or dedicated stochastic extensions of the CTM (Boel & Mihaylova, 2006), are theoretically better in reproducing instability and stop & go waves. However, there is no decisive argument available in literature on whether this actually results in better estimation and prediction performance.

2.3.2 Time series

Time series prediction involves modeling a variable as a function of its past observation and an error term. Instead of using traffic theory, statistical functions are used. Compared to other methods some of these methods have shown a high accuracy and a low computational effort, making some of them useful for short term predictions.

2.3.2.1 Linear regression

In linear regression the prediction function is assumed to be a linear combination of its covariates, where parameters indicate how much one covariate contributes to the outcome (e.g. Lan & Miaou, 1999 and Rice & van Zwet, 2004). Although the model is simple, in some cases it is shown to produce quite good results, as well as very fast predictions due to its simple form.

2.3.2.2 ARIMA

An ARIMA model, also called a Box-Jenkins model, is a common statistical technique that can be used for prediction (see e.g. Kirby et al., 1997 and Smith et al., 2002). Results of applying ARIMA are mixed; some studies report good results, some report the contrary. Many variations on ARIMA have been proposed in literature, such as SARIMA (see e.g. Guo, 2005), subset ARIMA (Lee & Fambro, 1999), Kohonen ARIMA (Voort et al., 1996), ARIMAX (Williams et al., 1999), VARMA (Min & Wynter, 2011) and STARMA (Kamarianakis & Prastacos, 2003) and Exponential Smoothing (Chrobok et al., 2004) in order to improve results. Some of these variations are indeed shown to improve prediction accuracy.

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[1] Several authors have elaborated the Bayesian recursive filter in a variety of manners, ranging from the simplest assumptions of Gaussian noise and linearized models, yielding Extended Kalman Filters (EKF), over Mixture Kalman Filters (MKF) that explicitly deal with mode switching in the CTM, to Unscented Kalman Filters (UKF) and Particle Filters (PF) that both allow non-Gaussian distributions of noise and system states and do not require approximation of the first order derivatives of system and measurement models. For practical applications, the simplest and computationally least stringent EKF is reported to be sufficiently accurate (van Hinsbergen et al. 2008; Wang et al., 2008).

2.3.2.3 Kalman filtering

A Kalman filter estimates the future state from only the estimated state in the previous time step and the current measurement (see e.g. Okutani & Stephanedes, 1984). Results are varying: the Kalman filters outperform some methods but sometimes the same models outperform Kalman filters.

2.3.2.4 ATHENA

In this model, developed by the French traffic and safety research institute INRETS, traffic is modelled as a linear combination of historical and current states. For each type of traffic a non-linear transformation is applied. This model outperformed several other models (Kirbey et al., 2004).

2.3.2.5 Gaussian Maximum Likelihood

A Gaussian Maximum Likelihood is based on the following two principles: (1) the prediction deviates as little as possible from the historical average, and (2) the predicted increment deviates as little as possible from the historical increment. Predictive performance is better than several other methods according to Lin (2001).

2.4 Non-parametric models

The term non-parametric does not imply that these models completely lack parameters, but rather that the number and nature of the parameters are flexible and not fixed in advance. Model structure as well as model parameters need to be determined from data. Therefore, usually more data is required than for parametric models. The advantage of these models is that the difficult, dynamic and non-linear processes found in traffic can be modelled without knowledge on the underlying processes being required. Unforeseen cases such as incidents, however, pose a problem as the model structure is derived from data. What is striking is that only one of these methods has been applied network-wide; all other studies focus on predictions on one single location or one route due to lack of data on all roads. For DTM purposes, this is a major drawback.

2.4.1 k-Nearest Neighbor

With the k-Nearest Neighbor method, a historical database is searched every time for the k events which are nearest to the current traffic situation. The outcomes of the nearest events are averaged or weighed to their distance to the current situation (see e.g. Rice & van Zwet, 2004 and Kim et al., 2005). All studies show that it is a fast method that can outperform naïve prediction methods, but none finds it more accurate than more advanced methods.

2.4.2 Locally Weighted Regression

Locally Weighted Regression uses local regression models. The prediction residual of each data point is then weighted proportionally to its proximity to the current measurement. Very good results are reported (Nikovski et al., 2005 and Zhong et al., 2005) in prediction accuracy as well as computation time.

2.4.3 Fuzzy Logic

With fuzzy logic a rule base (a set of IF-THEN rules) is created, manually or automatically. A current situation corresponds to one or more rules. Based on the 'then' and sometimes the degree of correspondence, a prediction is made. While some studies find promising results, Huisken (2003) finds that Neural Network methods produce better predictions.

2.4.4 Bayesian networks

In Bayesian networks, also known as causal models, the data from adjacent links are considered informative to the current link under investigation (Zhang et al., 2004). A Bayesian network is simply a directed graphical model for representing conditional independencies between a set of random variables. Comparisons with other methods are not made.

2.4.5 Neural Networks

Neural networks are the most widely applied models to the traffic prediction problem, because they are capable of modeling non-linear and dynamic processes well. Many extensions on the basic concept have been implemented to improve prediction accuracy and/or reduce computational effort. These extensions can be subdivided by the type of variation: (1) a different training procedure, (2) different internal structures or mathematics, (3) pre-processing input data and (4) include spatial and/or temporal patterns explicitly into the models. Before these extensions are dealt with, first the “standard” neural network is described.

2.4.5.1 The “standard” Neural Network

The Back Propagation Neural Network (BPNN) is more or less the “standard” neural network approach, and when a variation is applied, usually the models are compared to the BPNN. The BPNN consists of an input layer, one or more hidden layers and an output layer. Training with back propagation means that there are two steps: (1) input is fed to the hidden layer; one or more outputs are produced as the response of the network; (2) this response is then compared with the desired output, and the difference (the error) is propagated backwards through the network. During this phase, the weights of the connectors are adjusted. This process is repeated until weights stop being adjusted and the errors remain constant. Many studies use BPNNs to predict traffic data, e.g. Huisken & van Berkum (2003) and Ishak & Alecsandru (2004). Results are good, although almost all extensions, which will be treated next, improve results even more.

2.4.5.2 Different training procedures

The Conjugate Gradient Algorithm (CGA) uses another way of adjusting weights when back propagating errors through the neural network. The most widely known CGA is the Fletcher-Reeves update (see e.g. Innamaa, 2005). Results are comparable to the standard BPNN. Evolutionary Learning is inspired by the theory of evolution. Neural network “individuals” can reproduce and/or compete with other individuals. Strong individuals with good predictions survive longer and/or reproduce more. The “fittest” individual will be chosen as the predictor (see e.g. Zhong et al., 2005). These Evolutionary Neural Networks (ENNs) show very positive results. Compared to the standard BPNN, training is much faster and prediction accuracy is higher.

2.4.5.3 Different internals

A Modular Neural Network (MNN) is based on a ‘divide-and-conquer’ strategy Ishak & Alecsandru (2004). The input is processed in several sub networks, each specialized in a certain task. MNNs are faster to train and can improve results (see e.g. Innamaa, 2005). Radial Basis Frequency Networks (RBFNN) use the Euclidean distance between the hidden neuron centre and the input vector (e.g. Huisken, 2003). Results show a slightly positive preference of RBFNN over BPNN. Inside the hidden layer of a Neuro-Fuzzy Network (NFNN), Fuzzy Rules are defined automatically (e.g. Xiao et al., 2004). Results are comparable to or better than those of the BPNN. In a Counter Propagation Neural Network (CPNN), at each iteration the inputs are assigned to one node using a distance measure (Dharia & Adeli, 2003). Training time is dramatically decreased and performance is slightly improved.

2.4.5.4 Pre-processing input data

Wavelet transformation is generally used for de-noising data (Xiao et al., 2004). A Wavelet Neural Network (WNN) uses wavelet functions instead of the standard sigmoid function used in BPNN (Xie & Zhang, 2006). Improvements in prediction accuracy as well as computational effort are found (Li, 2002). The Spectral basis Network (SNN) employs a Fourier expansion of the input vector to obtain linearly separable input features (Rilett & Park, 2001). This new input vector is fed to a standard BPNN model. Improvements in prediction accuracy are found, especially on longer prediction horizons. The Generalized Neural Network (GNN) also uses a Fourier expansion of the input vector. The hidden neurons however are replaced with intelligent neurons which have an increased storage capability (Tan et al., 2004). In convergence and in accuracy, the GNN is found to be better than the BPNN. A Kohonen Self Organizing Feature Map Network can be used to cluster input data before feeding it to a standard BPNN (Park & Rilett, 1998).

The Kohonen SOFM is itself a neural network, containing only input nodes and output nodes and no hidden layer. The Kohonen SOFM BPNN is found to outperform a standard BPNN, but is in its turn outperformed by a Fuzzy c-means Clustering Network (FCNN) (Park & Rilett, 1998). The FCNN clusters the input data before feeding it to a standard BPNN. The FCNN outperformed a number of other neural network applications and other techniques. In a Principal Component Analysis Neural Network (PCANN), the input vector data is “compressed”, reducing the number of inputs and therefore improving the BPNN performance (Ishak & Alecsandru, 2004). CoActive Neuro-Fuzzy Inference Systems (CANFIS) combine features of the RBFNN and the FCNN and outperforms several other neural networks (Ishak & Alecsandru, 2004).

2.4.5.5 Include temporal/spatial patterns

The Jordan/Elman network or Simple Recurrent Network (SRNN) contains memory units that are used to store the hidden-layer output signals at the previous time step, providing a mechanism to recognize recurring patterns (e.g. Ishak et al., 2003). Results are similar to other improved neural network topologies. The Partially Recurrent Network (PRNN) is a simplified version of the Jordan/Elman network (see e.g. Ishak et al., 2003) and shows equal performance to other neural networks. The State Space Neural Network is a special version of the Partially Recurrent Elman network (e.g. van Lint et al., 2002). The neurons in the hidden layer all represent a certain link of an entire route. The weights of a hidden neuron can be interpreted as the link travel times.

The SSNN outperforms naïve methods drastically (van Lint & Schreuder, 2006) but is not compared to other neural network types. In contrast to the BPNN, in the Finite Impulse Response Network (FIRNN) the static weights are replaced by linear filters which have tapped delay lines in it, so to capture the internal dynamics of the traffic processes (Yun et al., 1998). The FIRNN outperforms BPNN, but is outperformed by a Time Delay Recurrent Network (TDRNN) where the previous output values are fed back into the input values (see Yun et al., 1998). The Time Delay Feedforward Network (TDFNN) has memory only at the input layer. It is composed of feed forward arrangement of memory and nonlinear processing elements. Results are good (see Alecsandru, 2003 and Ishak et al., 2003), but the Locally Weighted Regression model performed better (Zhong et al., 2005).

2.5 Conclusions

An overwhelming amount of different methods have been developed. It can be concluded that not one of the methods can be considered the best method in any situation, let alone under all possible situations. Under some conditions the linear regression, the Locally Weighted Regression model, and Evolutionary Neural Networks have shown good performance in comparison to other methods in prediction accuracy and in computational effort.

What is striking is the small number of methods that have been applied network wide and in both urban and freeway environments. After all, for most practical applications, such as trip planning for transport companies, route advice in consumer products and large scale Dynamic Traffic Management, network wide predictions in all environments are a necessity. The vast majority of studies however have focused on predicting traffic on a single location or fixed routes on freeways. In order for the methods to be used in practice they should be able to predict traffic on a much larger scale. An important advantage of traffic simulation models is therefore that they can be used for network-wide traffic predictions. Moreover, because traffic flow models capture the fundamental properties of traffic flow, they improve consistency between measurements, guaranteeing physical principles like conservation of vehicles on links and over nodes. This also renders them capable of modeling unforeseen situations such as incidents, which pose a problem for non-parametric models.

Traffic simulation models seem to be an isolated research topic. In no study a comparison is made between a traffic simulation model and any other method. This can be due to the difference in scale as mentioned before. Nevertheless it would be interesting to see how time series or non-parametric approaches would perform in comparison to traffic simulation models, on certain links or on a network wide scale.

3 Decision Support Systems

3.1 Introduction

The purpose of a Decision Support System (DSS) is to aid traffic operators in selecting appropriate traffic control measures (see SECTION for an overview of the various possibilities) given the current and shortly expected traffic conditions. To obtain an estimation of the future traffic conditions, prediction models are used (see the overview in SECTION). To fulfill this purpose, a DSS generally performs the following tasks (Hoogendoorn et al. (2003) and Ossowski et al. (2002)):

- Identification of problems:
  - Monitoring: This step involves the automatic collection and processing of all data. This includes traffic measurements (speeds, flows, densities) but also additional information may be obtained, for instance from a dialogue with the traffic operator.
  - Diagnosis: The problem, i.e. the situation that (possibly) requires a control action, needs to be identified and described (e.g. location, type, cause) given the available data.
- Proposal of control alternatives: Various decision alternatives are to be selected to try to remedy the observed problem.
- Prediction: A forecast is made of the expected traffic conditions given the current conditions, the predicted demands and the proposed control scenarios. For this, a traffic prediction model is used.
- Advise: The DSS suggests a control scenario that is expected to produce the best results to the operator. Often, a ranking of several control options is presented, based on the score on some or several performance indicator(s).

While some articles presenting DSS have been found, the scientific literature on this subject is somewhat limited. Arguably, expertise regarding DSS is more present in commercial companies than in the academic world. In the following, a brief discussion of the investigated scientific articles is provided.

3.2 Overview of Scientific State-of-the-art

Knowledge-based decision support systems use heuristic rules (of thumb) defined from expert knowledge to identify viable control actions responding to the observed traffic conditions. One of the earlier knowledge-based decision support systems for traffic control is the Freeway Real-Time Expert System Demonstration (FRED), see Ritchie (1990) and Zhang & Ritchie (1994). The applicability of these early developments was rather limited.

Logi & Ritchie (2001) proposed the ‘Traffic Congestion Manager’ (TCM). TCM uses real-time traffic data and knowledge-based rules to identify and characterize problems (mainly based on location and problem type). Then, possible control actions are selected from a predefined database, based on a strategy appropriate to the identified problem. The expected impact on traffic flow is estimated based on current and expected information on demand and supply. This evaluation is performed with simple models composed from HCM guidelines and experts’ rules of thumb. Also, the compatibility between problems, goals and control solutions is analysed. Viable control responses are then proposed to the operator, along with an explanation of the reasons process that led to their selection and an estimation of their expected impact.

Another knowledge-based decision support system is the TRYS system presented by Cuena et al. (1995) – see also Molina et al. (1998) and Hernandez et al. (2002). TRYS divides a network in several (overlapping) sections to which agents are assigned. An agent detects problems in their section and proposes control actions to a higher level coordinator. This coordinator combines the local proposals into global control actions. The TRYS system applies fuzzy logic in its decision process, which has the advantage that it can deal with situations that are not entirely covered by the knowledge base (De Schutter et al. (2003)).

Another approach is case-based decision support. Herein, solutions to the current problem are selected based on the solutions of similar past problems. These are the cases, describing the impact of control actions under specific conditions. After implementing a control solution to the current problem, the resulting situation can be added to the case base. This means that case-based DSS is a continuous step-wise learning procedure (Aamodt & Plaza, 1994). Case-based DSS can be formulated as four steps:

1. Retrieve cases in the case base that are relevant to the current problem
2. Map the solutions from the selected cases to the current problem (e.g. with fuzzy logic)
3. Test the new solution (in real-life or in simulation) and if necessary, revise it
4. Keep the resulting experience as a new case for future decision support

A case-based DSS is presented in Hoogendoorn et al. (2003) and De Schutter et al. (2003). This is a multi-agent DSS that divides the network into sub networks. Each sub network has its own case base and an evaluation agent. The case bases contain specific situations that have occurred in the sub network, and describe the relation between the input (the circumstances and the applied control measures) and output (the performance) of the sub network for these situations. Traffic control measures are subdivided in global measures (e.g. route guidance) that have an effect on the entire network and local measures (e.g. ramp metering or variable speed limits) that mainly have an impact within the sub network. If a problem has been identified and diagnosed, it is determined which cases (for each relevant sub network) are the most similar to the current situation. This similarity is described by similarity function based on fuzzy membership functions.

The predicted performance of a control scenario to the current problem is then estimated as the weighted average – using the similarity functions as weights – of the performances of this control scenario in the considered cases. The total network performance is obtained as a weighted average of the sub network performance – the weights being the relative importance of a particular sub network to the total performance. Based on (weighted sum of) the selected performance criteria (e.g. total time spent, maximum throughput) a ranking of the best control measures is suggested to the operator. Finally, De Schutter et al. (2003) state that the purpose of their methodology is to limit the possible combinations of control measures to only a few, which deserve further evaluation (for instance by a real-time traffic simulation model).

The DSS presented in Krishnan et al. (2010) works according to the same principles as case-based DSS, in the sense that past performances in similar situations are used to suggest control measures for a current problem. Instead of using a case base, a pattern-matching component is applied to identify similar past traffic conditions. Krishnan et al. (2010) combine a state estimation model and a rule set to identify problems. A so called rule engine then determines the course of action: either a pre-defined control measure is suggested based on some rule, or the pattern-matcher is addressed. This pattern-matcher is essentially a k-Nearest Neighbour (k-NN) tool that - using the Advanced Uncertain Reasoning Architecture (AURA) technology (AURA, 2010) to decrease computation time - rapidly searches historic traffic datasets, finding (sets of) control measures applied in time periods with similar traffic conditions. The best solution(s) to the current problem is then selected as the one among these past control measures maximizing the performance. The performance is calculated during a pre-defined number of time periods after each control measure was applied.

Finally, Almejalli et al. (2007) propose a DSS that uses a fuzzy neural network approach to suggest a ranking of control measures to the operator. A fuzzy neural network approach adopts the learning procedure from the neural networks to determine the fuzzy logic parameters (e.g. fuzzy memberships). A genetic algorithm is used to generate the fuzzy rules needed to build the fuzzy neural network. The current traffic conditions and an offline generated set of possible control actions is input to the pre-trained fuzzy neural network tool. This tool then predicts the performance of each control measure. A weighted aggregate performance is obtained from several criteria such as queue lengths, total travel times, fuel consumption and so on.

3.3 Conclusions

Several DSS found in the literature have been described. Articles that extensively review and categorise earlier work were not found. Also comparative studies are lacking, which makes it difficult to assess the validity of the various existing approaches.

Most approaches are either knowledge-based (operating on expert rules) or case-based (building on past example cases). Case-based approaches have the advantage of providing decision support based on actual (past) observations instead of predefined knowledge-based rules of thumb. On the other hand, the validity of the case-based DSS seems to strongly depend on the quality of the case base. Almejalli et al. (2007) use fuzzy rules composed via genetic algorithms in a neural network tool.

Fuzzy logic is used by the majority of DSS. Fuzzy systems have the advantage of being able to generate decisions for situations that are not explicitly covered by the reference base.

Many DSS adhere a multi-agent architecture, often dividing the network in smaller sub-networks. This renders the methodology scalable to large networks. However, caution is needed to ensure consistency between the predictions for different sub-networks, i.e. the boundary conditions must match (De Schutter et al., 2003). Ossowski et al. (2005) provide guidelines for the construction of agent-based DSS. Dunkel et al. (2011) do the same for a event-driven framework for DSS, but they fail to clearly indicate the difference and benefits of their suggested approach compared to existing DSS.

Finally, all examined studies select (or rank) control measures from a pre-defined set of possible control interventions. None seem to generate a detailed control scenario from scratch.

4 Traffic Control Algorithms

4.1 Introduction

This chapter provides a literature survey of co-ordinated traffic control strategies, both for freeways and urban roads. It is an edited version of an existing report with permission of the authors:

S. Lin and B. De Schutter, A survey on coordinated traffic control, Tech. Report 09-054, Delft Center for Systems and Control, Delft University of Technology, Delft, The Netherlands, December 2009, Report for the Centre for Transport and Navigation (DVS) of the Dutch Ministry of Transport, Public Works and Water Management.

The coordinated traffic control strategies are classified into different categories according to the control methodologies adopted, i.e. optimal control approaches, Model Predictive Control (MPC) approaches, rule-based approaches, case-based approaches, and approaches based on the network macroscopic fundamental diagram.

4.2 Optimal Control

The main idea of optimal control is to find the optimal control measures of the whole freeway network in the future by optimizing the cost function based on a network model for a certain future time horizon. The optimal control approach can coordinate the freeway network in a centralized structure. It not only can coordinate the control measures on different space locations and different time points in the future, but it can also coordinate different types of control measures (e.g. ramp metering, speed limits, and route guidance). Optimal control approaches for freeway networks and urban networks are both discussed below.

4.2.1 Freeway Networks

AMOC (AdvancedMotorwayOptimal Control) (Kotsialos and Papageorgiou, 2004b) and OASIS (Optimal Advanced System for Integrated Strategies) are two control software tools based on optimal control theory. They both adopt the macroscopic freeway traffic model METANET (Messmer and Papageorgiou, 1990) as optimization model. However, because the freeway network model is nonlinear, one of the big challenges of applying optimal control is to find an efficient algorithm to solve the large-scale optimization problem. A numerical solution algorithm that is based on a feasible-direction nonlinear optimization method, is proposed to successfully solve this problem (Kotsialos and Papageorgiou, 2004a,c; Kotsialis et al, 2002). The AMOC approach has been applied to the Amsterdam ring-road, and proved to have good coordination control effectiveness.

4.2.2 Urban Networks

In recent years, a number of urban traffic models have been proposed. For different urban traffic models, different optimal control approaches have subsequently been derived. The store-and-forward model is a linear state-space model for road networks of arbitrary size, topology, and characteristics. The linear state-space feature of the store-and-forward model opens the way to the application of a number of highly efficient optimization and control methods (such as linear programming, quadratic programming, and multivariable regulators) with polynomial complexity. Based on the store-and-forward model, an open-loop quadratic-programming control (QPC) (Aboudolas et al., 2009) approach was developed, which can be efficiently solved by using broadly available codes of commercial software.

However, to keep the linear characteristic, the store-and-forward model is only applicable under a saturated traffic scenario. Therefore, an open-loop nonlinear optimal control (NOC) approach is developed based on a nonlinear urban traffic model, which is more elaborate to describe more complex traffic dynamics. A numerical feasible-direction optimization algorithm is applied to solve the nonlinear optimization iteratively, which requires more computational complexity than QPC.

To avoid the inherent drawbacks of an open-loop structure, a linear-quadratic (LQ) optimal control approach, Traffic-responsive Urban Control (TUC) (Aboudolas et al., 2009; Dinopoulou et al., 2006; Kosmatopoulos et al., 2006), was developed based on the store-and-forward model. Instead of optimizing the control inputs (i.e. green times), TUC optimizes the linear multivariable feedback regulator off-line, as

$$\mathbf{g}(\mathrm{k}) = \mathbf{g}N - \mathbf{L}\mathrm{x}(k) \tag{1}$$

where the feedback gain matrix L results as a straightforward solution of the corresponding algebraic Riccati equation, and gN is a nominal vector for g. The feedback regulator is actually a feedback control law, which is assumed to be a linear function of the traffic states x(k) for the linear traffic control problem presented in TUC. The parameters of the feedback control law, i.e. the feedback gain matrix L, can be obtained through off-line optimization. Then, the optimized feedback regulator can be actuated on-line to derive the new green times, fed with the real-time measured traffic states x(k), and no on-line optimization is needed.

Dynamic Intersection Signal Control Optimization (DISCO) (Lo et al., 2001) is a dynamic urban traffic optimization control approach based on the cell-transmission model. The timing plans of the urban traffic network are derived by solving the optimization problem via a genetic algorithm. DISCO is proved to be superior to TRANSYT, especially under congested situations.

In spite of all the advantages, the optimal control approach is still open-loop. It solves the optimization problem based on the approximation of the future network disturbances, which can be inaccurate, or even be the opposite to reality when unpredictable events occur. Moreover, mismatches between the model and the real world, and inaccuracies in estimating initial traffic states can always happen. Under these circumstances, the control results derived from optimal control methods are not the best coordination control actions anymore.

4.3 Model Predictive Control (MPC)

Model Predictive Control (MPC) (Camacho and Bordons, 1992; Maciejowski, 2002) is a methodology that implements and repeats optimal control in a rolling horizon way. This means that, in each control step, only the first control sample of the optimal control sequence is implemented, subsequently the horizon is shifted one sample and the optimization is restarted again with new information of the measurements. The optimization is calculated based on the prediction model of the process and of disturbances.

Taking optimal control as the core algorithm, MPC preserves all the advantages of optimal control. It can predict and find the coordinated optimized solution for the entire network in the future. It can also coordinate different types and numbers of control measures. Due to the rolling horizon methodology, the MPC controller becomes closed-loop by adjusting the controller with a real-time feedback. The MPC controller thus obtains the ability to deal with the uncertainty of the real world, caused by unpredictable disturbances, (slow) variation over time of the parameters, and mismatch errors of the prediction model. In principle, a centralized MPC method can maximize the throughput of the whole network or any other objective function, and provide network-wide coordination of the traffic control measures. However, the real-time computation complexity is a big challenge for implementing MPC controllers to traffic networks in practice. In general, the computational complexity will increase exponentially when the scale of the network grows (if the prediction model is nonlinear). To overcome this problem, different structures (e.g. decentralized and hierarchical structures) other than the original centralized structure are taken to maintain the real-time feasibility of MPC controller.

4.3.1 Centralized Structure

Freeway Networks

(Hegyi et al., 2005a,b) apply MPC taking METANET as the predictive model to control and coordinate the freeway networks in the centralized structure (see Figure 2). To suppress shock waves, coordination of variable speed limits is studied adopting the MPC methodology. Simulations are carried out on a benchmark network consisting of a link of 12 km, where 6 segments of 1 km are controlled by speed limits. The simulation results show that the MPC controller is effective for coordinating speed limits against shock waves. The shock wave generated from the downstream end of link is successfully eliminated by the coordinated control of the speed limits.

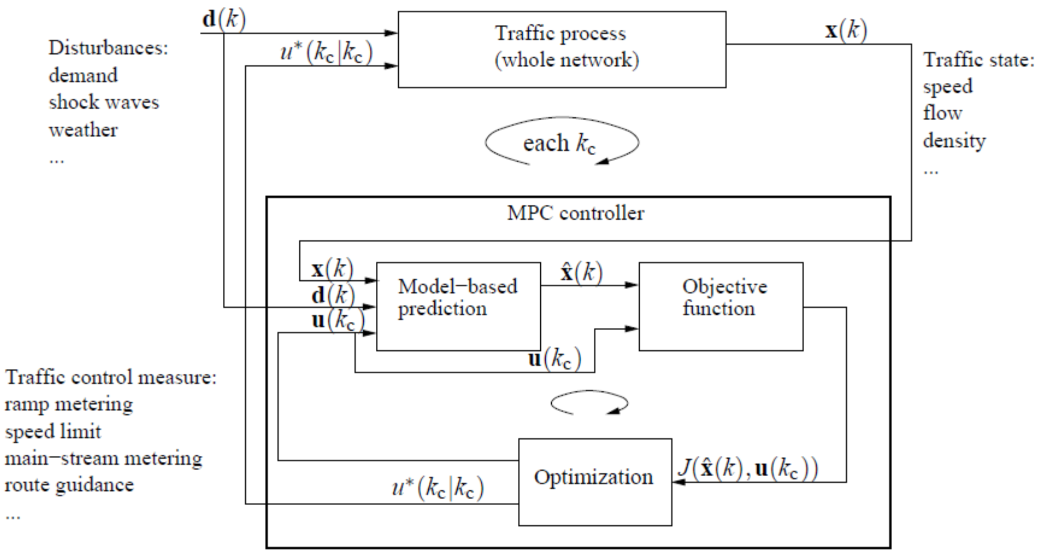


Figure 2: The MPC scheme for traffic control (Hegyi, 2004).

Experiment results show that the speed limits can complement ramp metering, when the traffic demand is so high that ramp metering alone is not efficient anymore. Conclusions are also drawn that the coordinated and integrated control of speed limits and ramp metering results in a higher outflow and a significantly lower total time spent.

Urban Networks

In the 1980s and 1990s, a number of model-based optimization control strategies emerged: OPAC (Gartner, 1994), PRODYN (Farges et al., 1983), CRONOS (Boillot, 1992), and RHODES (Sen and Head, 1997). The prediction models for these strategies are similar. They mainly predict the future traffic demands at the intersections through the historical data measured from the upstream detectors or the detectors of upstream links. These strategies showed advantages compared with the traffic-responsive strategies that do not use any predictions. However, this kind of prediction models is limited in the length of the time horizon over which they can predict. The longest prediction horizon is the time taken by the vehicles running from the upstream detector to the stop-line of the intersection. Therefore, the control strategies cannot look ahead far enough due to this limitation.

In recent years, some macroscopic urban traffic models were developed for establishing more elaborate and effective model-based rolling horizon control approaches. These models can describe the traffic dynamic mechanics of the whole urban traffic network, and overcome the drawbacks of the previous models.

The model proposed in (Barisone et al., 2002) and extended in (Dotoli et al., 2006) is computationally intensive and it can describe different traffic scenarios, but it is also complicated and needs historical data to estimate the coming traffic flow rate of each intersection. A controller based on a rolling horizon methodology is developed by optimizing this traffic model fed with the historical data from last iteration.

The model proposed by (Kashani and Saridis, 1983) has a lower modeling power, and in particular cannot depict scenarios other than saturated traffic. The model of (Hegyi, 2004; van den Berg et al., 2003, 2004) is an extension of the Kashani model that is capable of simulating the evolution of traffic dynamics in all traffic scenarios (unsaturated, saturated, and over-saturated traffic conditions) by updating the discrete-time model in small simulation steps. This model provides a good trade-off between accuracy and computational complexity. An MPC controller is developed, which gives good control effects.

Mixed Freeway and Urban Networks

Freeway networks and urban networks are closely connected. Congestion on the freeway often causes spill back of urban queues, slowing down the urban traffic, and vice versa. As a consequence, control measures taken in one of the two areas can have a significant influence on the other area. By connecting the urban traffic model (van den Berg et al., 2004) and the freeway traffic model METANET with the on-ramp and off-ramp model, an integrated MPC controller is established to coordinate the mixed freeway and urban network (van den Berg et al., 2007). The coordinated control approach is proved to have a high performance.

4.3.2 Distributed Structure

Freeway Networks

A distributed control structure can be developed to avoid the exponential growth of the computational complexity for the centralized MPC, when the network scale keeps on increasing. Game theory has been introduced to find the optimal coordination of ramp metering and variable speed limits in a large-scale freeway traffic network (Ghods and Rahimi-Kian, 2008). The large-scale freeway traffic network is then decomposed into sub problems, each of which is controlled by MPC based on the METANET model. Game theory (i.e. sample fictitious play, SFP) coordinates the sub-MPC controllers.

In (Ghods and Rahimi-Kian, 2008), for a case study of 4 players (i.e. 2 on-ramp metering controllers and 2 speed limit controllers), the SFP-MPC, which can compute in parallel, reduces the optimization time by 81.1%, from 106 s to 20 s, compared with the original centralized MPC controller.

Urban Networks

Game theory is also used as distributed control method for urban networks in CoSIGN (Cheng et al., 2006). The decomposition of the problem can be accomplished by assuming that each signal in each period is an independent decision maker. To coordinate the decision makers (traffic signals), game theory is applied. If each decision maker who controls a time period for a signal is viewed as a player in the game, and the average travel time of all vehicles in the traffic network is viewed as a common payoff for every player, the coordinated-traffic-signal-control problem can then be represented as a game of identical interests. The Nash equilibrium of this game can be viewed as a coordinated local optimum. The equilibrium situation is not always uniquely determined and it is even possible that oscillations occur. Moreover, equilibrium may not always be a system optimum (Taale and van Zuylen, 1999).

4.3.3 Hierarchical Structure

Freeway Networks

Due to the open-loop nature of the optimal control approach AMOC, the derived optimal control actions are deteriorated by all kinds of system errors, such as initial states estimation error, future disturbance prediction error, model parameter mismatch error, and unpredictable incident errors. Therefore, Kotsialos et al. (Kotsialos et al., 2005) proposed an MPC approach based on the AMOC algorithm under a hierarchical control structure.

The hierarchical control structure consists of three basic layers (see Figure 3): the Estimation/ Prediction Layer, the Optimization Layer, and the Direct Control Layer. The Estimation/ Prediction Layer receives historical information and real-time detected traffic states to generate the current state estimation and future predictions of the disturbances for the next layer. The Optimization Layer (AMOC) optimizes the control state trajectory over a future time horizon based on the initial states estimation and future disturbance prediction from the upper layer. Then, in the Local Direct Layer, the local ALINEA (Asservissement LINéaire d'Entrée Autoroutière) controller is adapted by the real-time optimized traffic set points obtained from the upper Optimization Layer. ALINEA is a local proportional ramp metering control strategy with feedback (Papageorgiou et al., 1991).

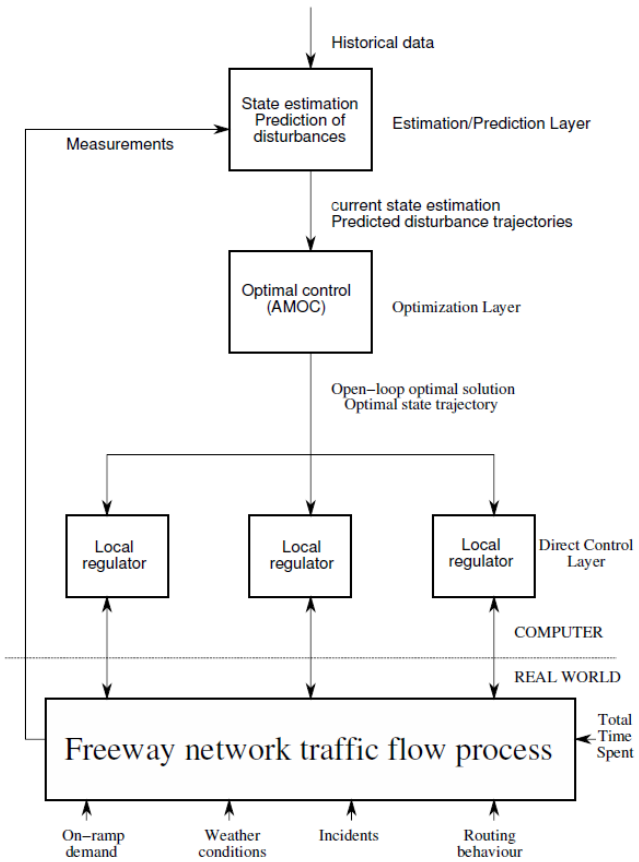


Figure 3: Hierarchical structure (Kotsialos et al., 2005)

The rolling horizon hierarchical coordinated control has been applied to the Amsterdam ring-road, and outperforms the local ramp metering approach in terms of both efficiency and equity (Kotsialos et al., 2005). The combination of AMOC with ALINEA preserves the positive features of both and cancels their deficiencies.

Urban Networks

A hierarchical control structure divides the complex control problem of a large traffic system into different control levels or layers. In different layers, control problems with different focuses are solved. Moreover, control problems with different details are addressed in different levels, e.g. the lower control level mainly focuses on local control in a more elaborate way, and the higher control level deals with network-wide coordinated control in a more general way.

Examples of urban hierarchical control structures include: Virtual-Fixed-Cycle OPAC (VFC-OPAC) (Gartner et al., 2001), the hierarchical version of OPAC and RHODES multi-level hierarchical variant (Mirchandani and Head, 2001). Both algorithms are conceptually similar, in that they consist of a three-layer architecture. The local layer calculates optimal signal switching sequences in a rolling horizon way, subject to constraints set by the higher levels. The middle layer coordinates the local controllers by optimizing offsets, while at the highest layer, synchronization takes place based on changing traffic conditions.

In (Van Katwijk, 2008) a hierarchical traffic control structure is developed. For the bottom level, a multi-agent approach is applied to reduce the computational complexity, and to add scalability to the control system. For the upper level, the local controllers are coordinated in both the microscopic and the macroscopic way. The traffic control problem is divided into several loosely coupled sub problems, such that the combination of all the solutions of the sub problems together approximate the solution of the original control problem. Each piece of infrastructure is represented by an agent that tries to attain its local objective in close cooperation with other agents.

4.4 Rule-Based Strategies

Rule-based systems solve a problem using “if-then” rules (Hayes-Roth, 1985, Russell and Norvig, 2003). These rules are constructed using expert knowledge and stored in an inference engine. The inference engine has an internal memory that stores rules and information about the problem, a pattern matcher, and a rule applier. The pattern matcher searches through the memory to decide which rules are suitable for the problem, and next the rule applier chooses the rule to apply. These systems are suited to solve problems where experts can make confident decisions. However, these systems work only with already created rules and in their basic implementation do not involve learning.

4.4.1 Freeway Networks

HERO

When the congestion is imported from downstream, local ramp metering almost has no effect. To this end, coordinated control strategies are needed. HERO (HEuristic Ramp metering coOrdination) (Papamichail and Papageorgiou, 2008) is a simple rule-based coordinated ramp-metering strategy that applies ALINEA for the local regulators. HERO can coordinate freeway networks of arbitrary size, including a string containing a number of successive ramps. When the queue on a ramp with active metering exceeds a threshold so that it may soon reach the maximum admissible value, this ramp is defined as the master ramp. Coordinated control actions are then adopted at the slave ramps (the upstream ramps). The queue lengths of the slave ramps are increased to stay close to the queue length of the master ramp. In this coordinated control algorithm, the slave ramps hold back some traffic so as to release the pressure from the master ramp, and prevent congestion. When the relative queue of the master ramp decreases below a certain threshold again, the coordination stops.

The ALINEA-based HERO is shown to outperform the uncoordinated local ramp metering and approximate the efficiency of the sophisticated optimal control schemes (e.g. AMOC) without the effort for real-time modeling calculations or external disturbance prediction.

ACCEZZ

Fuzzy logic systems, like humans, can handle situations where the available information about the system is vague or imprecise (Klir and Yuan, 1995; Nguyen and Walker, 1999). To deal with such situations, fuzzy sets are used to qualify the variables of the system in a non-quantitative way. The membership degrees can then be used to combine various rules and to derive conclusions. This process consists of three parts: fuzzification, inference, and defuzzification. Inference uses a set of rules based on expert opinions and system knowledge and combines them using fuzzy set operators such as complement, intersection, and union of sets. Fuzzy systems are often combined with other AI techniques for their complete deployment.

ACCEZZ (Adaptive and Coordinated Control of Entrance Ramps with Fuzzy Logic) (Bogenberger et al., 2002) is a rule-based algorithm for coordinated ramp metering. In order to coordinate the local fuzzy ramp metering controllers, the shape of each input or output fuzzy set at each on-ramp location of the metered freeway is adjusted dynamically. So, one way of modifying the behaviour of the ramp metering algorithm is by recalibrating the parameters of each fuzzy set, i.e. redefining the linguistic variables. Learning/ optimization methods obtained from neural network theory or evolutionary algorithms are used to find the optimal parameters of the fuzzy sets aimed at minimizing the Total Time Spent in the metered freeway system. The macroscopic traffic model METANET was used to evaluate the different coordinated ramp metering strategies, and helps to find the best system-wide strategy. Alternatively, a genetic algorithm can be used to determine the optimal coordinated parameters of the fuzzy ramp metering controllers based on macroscopic traffic model METANET. The resulting systems are either called neuro-fuzzy or genetic fuzzy ramp metering.

Comparing with five other standard ramp metering algorithms, i.e. demand-capacity, occupancy strategy, ALINEA, Denver's HELPER algorithm, and Minnesota's Zone approach, all developed versions of the ACCEZZ model family substantially improve the traffic conditions for the freeway analyzed.

4.4.2 Urban Networks

Fuzzy Rule Control System

Similar to ACCEZZ for freeway networks, fuzzy-logic controllers with genetic algorithms or neural network algorithms as adapting approaches for the fuzzy rules are also applied in urban traffic systems.

In (Heung et al., 2005), a decentralized urban traffic structure is proposed. It applies a fuzzy-logic controller as local intersection controller, and a dynamic-programming technique to coordinate the control results obtained from fuzzy-logic controllers and to derive the green time for each phase in a traffic-light cycle. In each fuzzy-logic controller, a GA algorithm is applied to learn and update in real-time the fuzzy sets.

A more complex urban network control hierarchical architecture is given in (Choy et al., 2003) based on a fuzzy neural decision support principle. The architecture consists of three layers. The lowest layer consists of intersection controller agents that control individual, pre-assigned intersections in the traffic network. The middle layer consists of zone controller agents that control several pre-assigned intersection controller agents. The highest level consists of one regional controller agent controlling all the zone controller agents. In each layer, every agent can obtain traffic data and make decisions autonomously. Both lower layer agents and upper layer agents can send cooperative factors (requests) to each other.

4.4.3 Mixed Freeway and Urban Networks

HARS

HARS (Het Alkmaar RegelSysteem) (Krikke, 2006; Vrancken and Ottenhof, 2006; Vrancken et al., 2007), which means "The Alkmaar Control System", is a state-of-the-art traffic management system implemented in the Alkmaar region in the Netherlands. The HARS system combines both a top-down traffic management strategy and a bottom-up traffic management strategy into a hierarchical traffic network management architecture. The two traffic management strategies complement each other. The top-down strategy makes decisions on the control schemes based on the predefined traffic scenarios stored in the expert database. In the bottom-up strategy, all road segments and nodes that connect the segments are defined as agents. The agent controllers compare their traffic state with a so called reference framework, which defines criteria that the traffic state on the link should meet. If the link's traffic state deviates from the reference framework, or will deviate in the near future, links will communicate via intermediate nodes with other links and ask them to reduce outflow in order to meet the criteria. If the upstream link is not able to adjust its outflow to make the downstream link meet the criteria, then it will forward the service-call to its upstream neighbouring link(s).

Alkmaar has two types of control measures: traffic light systems and Dynamic Route Information Panels (DRIPs). The DRIPs will be used for rerouting and informing drivers. The traffic light systems will be used as an instrument to change intensities of traffic flows.

4.5 Case-Based Strategies

Case-based reasoning, as the name suggests, solves a problem using the knowledge that was gained from previously experienced similar situations (cases) (Aamodt and Plaza, 1994; Ritchie, 1990). In this way, this technique learns the way a new problem is solved and stores the new solution in a database. A disadvantage of this approach is that it might not be clear what should be done for a case that is not yet present in the case base. However, new cases could be added on-line to deal with this problem.

To improve the existing dynamic traffic management systems, BSES (Boss Scenario Evaluation System) (De Schutter et al., 2003; Hoogendoorn et al., 2003a,b) based on fuzzy multi-agent case-based reasoning was proposed. BSES can evaluate control scenarios in real time, predicting their effects in terms of various measures of effectiveness, such as total travel time, vehicle loss hours, average speeds, fuel consumption, etc. The main characteristics of the system are 1) that it is case based, i.e., it uses either synthetic or real-life examples of the effect of control scenarios under different circumstances; 2) that it determines the similarity of the current situation to different examples in the case base using fuzzy logic, and 3) that it is agent-based, meaning that it predicts the effects of the different measures for small sub networks and combines these predictions afterwards.

Due to the exponential growth of the case base, straightforward application of case based reasoning to the decision support task is not feasible. Therefore, representative cases that can occur in practical situations are required to find out first how to reduce the case base scale. To address this problem, two aspects are introduced into the case-based reasoning framework: 1) Fuzzy logic is used to combine different cases in the case base (fuzzy case based reasoning); 2) The network to be controlled is divided in n partially independent sub networks for which the aforementioned fuzzy case-based reasoning approach can be applied. An iterative approach is used to find consistent solutions for the sub networks.

The main advantages of the BSES approach are the speed of computation (compared to using traffic flow models), the ability to use actual knowledge directly (rather than general knowledge or simulated data), and the ability to learn from previous experiences (continuous step-wise learning). It turns out that the system is able to very quickly produce predictions on the impact of different control scenarios to the traffic operations in the network, and that it can thus support operators in their decision tasks in a real-time decision environment.

4.6 Anticipatory Control Strategies Integrated with Traffic Assignment

Traffic control discussed so far generally refers to controlling the traffic control measures (e.g. traffic lights, traffic information, and ramp-metering) to reduce the traffic delay in the traffic network. However, the travellers inside the network may change their routes, when the new traffic control measures change the traffic in the network. Therefore, traffic control and the behaviour of the travellers influence each other. As a result, a new traffic control strategy is constructed by combining the traffic control problem with the traffic assignment problem. The new traffic control problem is formulated into a bi-level program in which the upper level deals with the control problem, and the lower level with the assignment problem.

In (Taale, 2008), an anticipatory control strategy is proposed to control and coordinate urban traffic networks by predicting the future traffic flows within the network taking the variation of the traffic assignment into consideration. As the traffic control and the behaviour of the travellers have different goals, game theory is applied to solve the bi-level optimization problem of the anticipatory control. The traffic control engineer and all the road users are then considered as two players. The traffic engineer controls the signal settings and the road users have route choice.

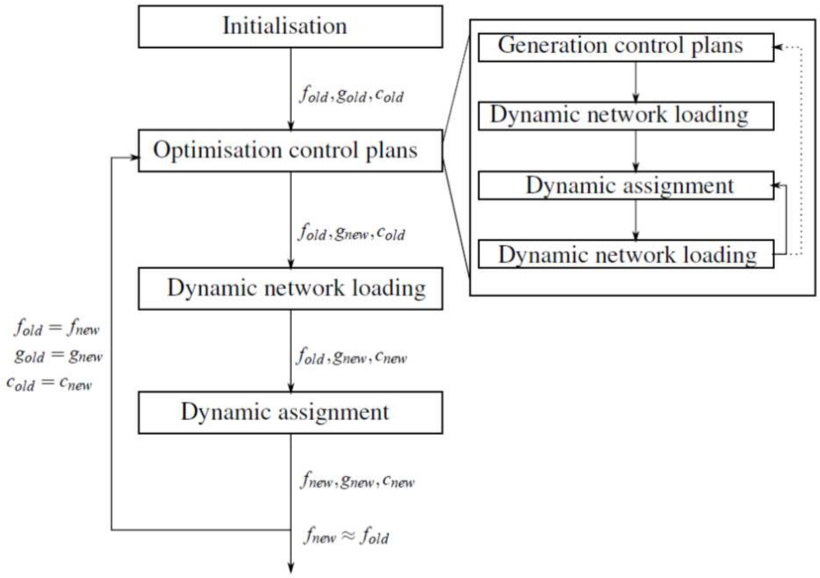


Figure 4: Framework for anticipatory control (adopted from (Taale, 2008))

Figure 4 illustrates the framework for developing, testing, and evaluating all kinds of network control strategies. The “optimization control plan” is the part where the anticipatory control strategy is determined. After the control plan is derived by certain algorithm, a simulation is started with a dynamic network loading model to see how traffic propagates through the network with this control plan; based on these results a dynamic traffic assignment is run to obtain a new route flow distribution, and again the dynamic network loading model is run to come to a final evaluation of the control plan.

4.7 Summary

From the view of traffic control methodologies, the existing coordinated traffic control strategies can be classified into MFD-based (Macroscopic Fundamental Diagram based) approaches, case based approaches, rule-based approaches, anticipatory control approaches, optimal control approaches, and MPC (Model Predictive Control) approaches under centralized, distributed, and hierarchical control structures.

Table 2: Comparison of the features for different traffic coordination control methodologies

Methodologies		Information	Control quality	Complexity	Integrated	Scalable	Application effort
MPC	Centralized	Global	H+	H	Yes	No	H
	Hierarchical	Compromise	H	H	Yes	Yes	H
	Distributed	Local	H	H	Yes	Yes	H
Optimal control		Global	M	H	Yes	No	H
Rule-based		Compromise	M+	L	Potentially	Yes	M
Case-based		Compromise	M+	M	Yes	Yes	M
Anticipatory control		Global	H+	H	Yes	No	H
MFD-based		Global	M-	L	Yes	Yes	L

H - High; M - Medium; L - Low; Compromise - between global and local

The main characteristics of the methods discussed above are summarized in Table 2 and Table 3. As Table 2 illustrates, in general, the more elaborate information that the controller takes into consideration, the better control result will be obtained. The centralized MPC approach makes use of the total global information by applying a traffic network model and feeding the model with real-time detected traffic states. So, the centralized MPC approach has the highest coordination control quality. However, it also has a high computational complexity at the same time, and needs more efforts to implement. Therefore, distributed and hierarchical MPC structures are developed to solve this problem by making some compromises. They give up a part of the global information to obtain simplified sub-problems, and improve the applicability of the approaches by controlling and coordinating the sub-problems. Moreover, a distributed structure also makes the controller scalable.

Table 3: Comparison of the coordinated traffic control approaches

Approaches			Control field	Control Feature						Control Structure			Control Measure				Control Objective		
				Model-based	Rule-based	Case-based	Optimization	Feed back	Prediction	Centralized	Distributed	Hierarchical	Ramp metering	Speed limits	Route guidance	Traffic signals	TTS like	Travel time	Delay
MPC	Centralized	Hegyi et al.(2005)[59]	F	✓			✓	✓	✓	✓			✓	✓			✓		
		van de Berg et al.(2004)[119]	U/I	✓			✓	✓	✓	✓						✓	✓		
		Dotoli et al.(2006)[42]	U	✓			✓	✓	✓	✓						✓	✓		
	Hierarchical	van Katwijk et al.(2008)[122]	U	✓			✓	✓	✓			✓			✓	✓	✓		✓
		Kotsialos et al.(2005)[73]	F	✓			✓	✓	✓			✓	✓				✓		
		OPAC[48]	U	✓			✓	✓	✓			✓				✓	✓		
		RHODES[97]	U	✓			✓	✓	✓			✓				✓	✓		
	Distributed	Ghods et al.(2008)[54]	F	✓			✓	✓	✓		✓		✓	✓			✓		
		CoSIGH[25]	U	✓			✓		✓		✓					✓		✓	
Optimal Control		AMOC[70]	F	✓			✓		✓	✓			✓		✓		✓		
		OASIS	F	✓			✓		✓	✓			✓			✓	✓		
		QPC[3]	U	✓			✓		✓	✓						✓	✓		
		NOC[3]	U	✓			✓		✓	✓						✓	✓		
		TUC[3]	U	✓			✓	✓	✓	✓						✓	✓		
		DISCO[90]	U	✓			✓		✓	✓						✓			✓
Rule-based		HERO[105]	F		✓			✓				✓	✓						
		ACCEZZ[16]	F	✓	✓		✓					✓	✓				✓		
		HARS[75]	I	✓	✓				✓			✓	✓		✓	✓			
		Febbraro et al.(2004)[39]	U	✓	✓		✓	✓	✓			✓				✓	✓		
		Heung et al.(2005)[61]	U		✓		✓					✓				✓			✓
		Choy et al.(2003)[26]	U		✓							✓				✓			✓
Case-based		BSES[38]	F			✓						✓	✓	✓					
Anticipatory Control		Taale et al.(2008)[116]	I	✓			✓	✓	✓			✓	✓		✓	✓		✓	✓
MFD-based		Rule-based	U		✓											✓			
		Proportion control	U					✓								✓			
		Anticipation control	U	✓			✓	✓	✓							✓			

F - Freeway; U - Urban; I - Integration of freeway and urban

Rule-based and case-based approaches are control strategies mostly based on historical information and expert experience. Because they are comparatively easy to implement, simple rule-based and case-based approaches first have been applied in traffic management system to coordinate traffic networks at the beginning. Moreover, they are the control approaches that are easy to coordinate all kinds of traffic control measures and manage large complex transportation systems. However, the control plans obtained by rule-based and case-based strategies are in general not optimal solutions. But, some smart rule-based and case-based control systems (e.g. HERO, ACCEZZ, HARS, BSES, etc.) can adjust themselves by updating their rules or databases according to the real-time measured traffic states or the predicted traffic states through the traffic models. This makes the rule-based and case-based approaches more adaptive to the variation of the real traffic.

In fact, when the traffic control plans change, the traffic flows in the traffic network will be reassigned, because the road users will also change their routes. Therefore, it is more realistic to also consider the traffic assignment while controlling the traffic. The anticipatory control approach constructs a bi-level program problem, in which the upper level deals with the control problem, and the lower level with the assignment problem. The control results of the anticipatory control are good because of taking the dynamic traffic assignment information into consideration. However, because of the iterative feature of the solver, the anticipatory control approach suffers the same drawback as the MPC control approaches, i.e. high computational complexity. Just like the centralized MPC, the anticipatory control can also be used for long-term traffic control and planning.

5 Discussion On Identified Open Issues

5.1 Introduction

In an internal meeting between FileRadar and KULeuven, the following open issues were identified:

- Fundamental diagram parameter estimation
- Prediction of ramp demand and split rates and estimation at unmeasured locations
- Alternatives to Extended Kalman-Filtering for state estimation

In the following sections, an overview is given on the literature that was found regarding these specific topics.

5.2 Fundamental diagram parameter estimation

This section provides a non-exhaustive overview of the state-of-the-art on estimation of the parameters of the fundamental diagram used in (first-order) dynamic network loading (DNL) models. The focus hereby is on the capacity C, since this parameter has the most influence on congestion formation. The other parameters, free-flow speed v_f and jam density k_j are very briefly discussed thereafter.

5.2.1 Capacity estimation methods

Before discussing various capacity estimation methods, a proper definition is needed of what exactly is ‘capacity’. The Highway Capacity Manual (HCM) defines capacity as the maximum rate of hourly flow that can traverse the uniform cross-section of a road segment under prevailing road, traffic and control conditions (Transportation Research Board, 1994). This definition does not clearly distinguish between the maximum flow rate of (free) flowing traffic (before a *breakdown*, i.e. a transition from a flowing to a congested traffic state at a bottleneck, occurs) and that of traffic accelerating from the head of a queue. We denote the former as *pre-queue capacity* and the latter as *queue discharge capacity*. The difference between the two is the *capacity drop*, which may vary from site to site and day to day. While other definitions of specific types of capacity may be found in the literature (see e.g. Minderhoud et al., 1997) we will use the above two definitions in the following.

While capacity in DNL applications is often regarded as deterministic, several studies acknowledge that capacity is in fact stochastic and a distribution should be considered rather than a single value (e.g. Ozbay & Ozguven, 2007; Geistefeldt & Brilon, 2009; Tu et al., 2010; Muralidharan et al., 2011). Firstly, the occurrence of breakdown is probabilistic in nature. Furthermore, the observed capacity values both pre-breakdown and after queue formation may vary strongly from day to day. This is influenced both by obvious and measurable factors such as incidents and weather conditions, but also unnoticeable or (almost) immeasurable variations in driver behaviour or vehicle characteristics or composition (e.g. percentage of trucks). Moreover, Muralidharan et al. (2011) point out that capacities are also significantly correlated across different sections.

Therefore, the analyst must choose between incorporating the stochasticity of capacity in the model and a deterministic model. In a deterministic model it should be decided whether or not to adopt dual capacities, or which one to choose (Dervisoglu et al., 2009).

The following overview collects both stochastic and deterministic capacity estimation methods. Also, some methods ignore the dual nature of capacity, while other methods focus on estimating either pre-queue or queue discharge capacity.

The following overview is largely based on that of Minderhoud et al. (1997), complemented with more recent studies. Minderhoud et al. (1997) distinguish various approaches based on data availability and requirements (Figure 5). The main categorization is between direct-empirical and indirect-empirical methods. The former type of methods estimate capacity from data measurements on the site. The latter can be used if data is lacking.

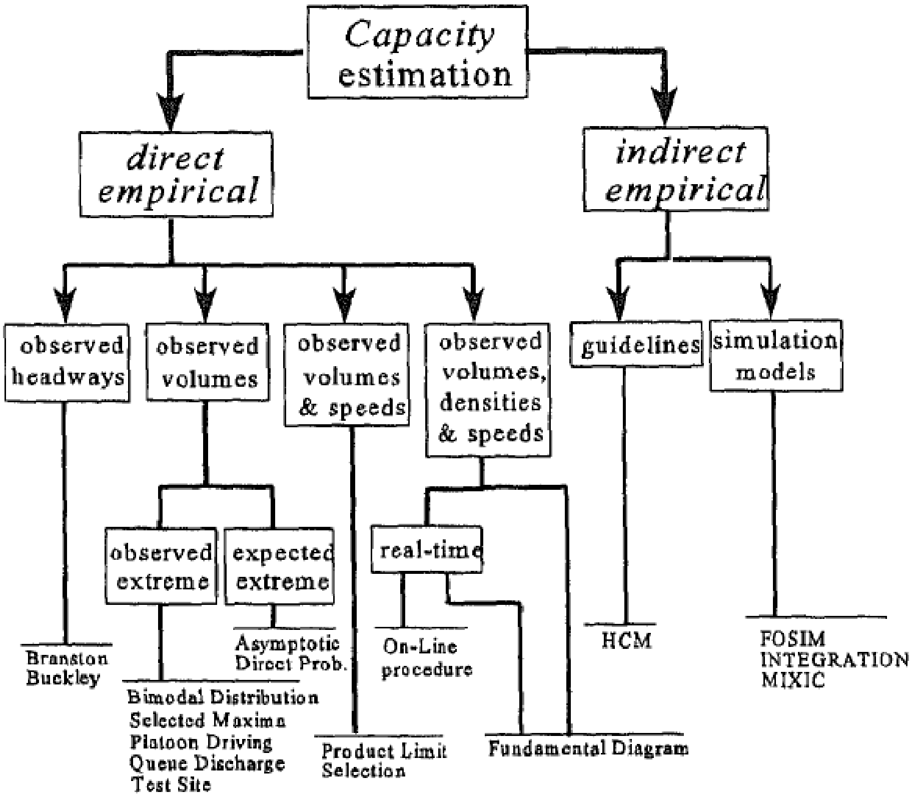


Figure 5: Classification of capacity estimation methods (Minderhoud et al., 1997)

The applicability of different methods depends not only on the type of data, but is influenced by other data characteristics such as the aggregation interval of the data, the location where data is collected (compared to the bottleneck's location) and the traffic conditions for which data is available. Before going into the methods themselves, these additional data characteristics are briefly discussed.

5.2.1.1 Factors influencing capacity estimation

Traffic conditions

Most methods require the flows corresponding to the capacity state itself to be measured. If such data is not available, the choice of a suitable estimation method becomes rather limited (e.g. the fundamental diagram method). Banks (2009) presents an automated procedure to identify periods of pre-queue and queue discharge capacity from flow and speed data.

Location of data observations

The location at which data should be observed is tied to the traffic conditions one wishes to observe. Most notably, location choice is important when estimating queue discharge capacity (e.g. with the empirical distribution method). In this case, congestion should occur upstream of the measurement location at the bottleneck. Downstream and at the measurement location, no congestion should occur to ensure that indeed the capacity of this bottleneck is measured and not the flow imposed by the spillback of some bottleneck further downstream (Minderhoud et al., 1997). For this, additional data such as speeds and/or densities are needed.

Data aggregation interval

The aggregation interval of the data is often chosen quite arbitrarily. One should bear in mind that small aggregation periods generally produce a higher capacity estimate than longer periods. Tu et al. (2010) find that 15-min aggregate capacity is 5% lower than 5-min aggregate capacity from empirical data on Dutch freeways.

According to the HCM (REF), a 15-min interval is considered to be the interval during which stable flow exists. Minderhoud et al. (1997) state that the 15-min interval is a good compromise between independence of the observations, smoothing local fluctuations and that the capacity can be maintained for longer than the applied aggregation interval (see also van Toorenburg, 1986). Regarding the impacts of short (less than 15-min) aggregation intervals on traffic flow rate, Qin & Smith (2001) state that stable flow rates may be calculated using aggregation intervals as short as 10 min and that statistically significant improvements in stability can be achieved by adding 2 min to any measurement interval. However, many studies use an aggregation interval of only 5 min (Ozbay & Ozguven, 2007; Geistefeldt & Brilon, 2009; Dervisoglu et al., 2009).

5.2.1.2 Direct-empirical methods

Headways, traffic volumes, speed, and density are traffic data types used to identify four groups of direct-empirical capacity estimation methods.

Estimation with headways

These methods derive a deterministic capacity value from the (distribution of) observed headways. They can be applied only per lane, but results per lane may of course be aggregated into a capacity value for a cross section. These methods are not discussed here, as usually intensity, speed and density data is more readily available on freeways than headways.

Estimation with intensity

Two approaches can be distinguished (see Figure 5). The observed extreme value methods use only known (observed) maximum traffic volumes as capacity estimates. The expected extreme value methods estimate capacities as higher-than-observed intensities using statistical methods. Some specific methods are mentioned below. None of these methods is recommended by Minderhoud et al. (1997). Therefore, these methods are only very briefly discussed.

Observed extreme:

- Bimodal: This method estimates capacity as the mean of the capacity part of a bimodal distribution of observed traffic flows – the first mode being measured demand below capacity and the second capacity flow rate. The problem is that it is difficult (and often arbitrary) to determine which distributions to assume, which depends strongly on the observation period. Moreover, this method can only be applied if indeed a clear bimodal flow distribution is observed.
- Selected maxima: These methods estimate the capacity based on the distribution of maximum flow rates measured in each observation period (e.g. each day). Some percentage value, e.g. the average or the 90th percentile may be assumed as the deterministic capacity value.

Expected extreme:

- Direct probability method: A prediction of the capacity (largest possible value) is made assuming that the traffic flows follow a theoretical model like the Poisson process. The resulting capacity estimate is to be considered as an exceptional, not-yet-observed extreme.
- Asymptotic method: This method is similar. Here, the capacity is estimated as the maximum flow rate predicted from the distribution of observed extremes in selected aggregation intervals.

For the above methods, the capacity estimate depends strongly on the duration of the aggregation interval. Moreover, since only intensities are used, it is very difficult to ensure that indeed capacity of the site is being measured – let alone which type (pre-queue or queue discharge) – instead of the demand or the flow in a queue spilling back from downstream. Minderhoud et al. (1997) state that the result of these methods is of little practical value for freeway modelling.

Estimation with intensities and speeds

These methods do take into account the traffic state, using the speed data. In particular for measuring queue discharge capacity of a site, it is crucial to know the traffic state upstream and downstream. We describe in the following the empirical distribution method, the product limit method, the maximum-likelihood method and the direct breakdown probability method.

The data points are placed into one of two categories: demand (free-flowing conditions upstream of the bottleneck) or capacity measurements (congestion upstream). The empirical distribution method uses only the capacity state observations. The capacity observations over the entire observation period are ordered, so that the empirical distribution function F of the capacity is obtained. F(q) indicates the probability that the capacity value is lower than a given value q. Often, a deterministic value for the capacity is taken at F(q) = 0.5 (the median). Munoz et al. (2004) choose the mean value. The empirical distribution method is well suited to estimate queue discharge capacity (Hoogendoorn & van Lint, 2006).

The product limit method is highly similar to the empirical distribution method. The difference is that it also extracts information from the demand measurements. The high-flow demand measurements are used to improve the empirical distribution function of capacity values. A function G(q) results that indicates the probability that the capacity is higher than q. F(q) then equals 1 – G(q). The general expression of the product limit method is (Minderhoud et al., 1997):

$$\begin{aligned}
&G(q) = \prod_{i:q_i \le q} \frac{K_i - 1}{K_i} \qquad q_i \in \{C\} \\
&with: \\
&K_i = number\ of\ observations\ with\ q \ge q_i\ (demand\ or\ capacity) \\
&\{C\} = set\ of\ observed\ capacity\ flow\ values
\end{aligned} \tag{0.2}$$

It should be noted that the above approach fails to acknowledge the capacity drop phenomenon (see Geistefeldt & Brilon, 2009). Indeed, from a demand measurement it is derived that the capacity corresponding to that observation should be at least equal to this demand measurement. However, the pre-queue capacity may be higher than the queue discharge capacity. Therefore, mixing this information with observations of the queue discharge capacity may lead to inconsistent result. Geistefeldt & Brilon (2009) reformulate the product limit method by only considering flowing measurements. G(q) is formulated similar to (0.2), however, $q_i \in \{B\}$ replaces the capacity observations. {B} is the set of breakdown observations, i.e. high intensities measured in a free-flow state after which a breakdown to a congested state occurred. This adapted product limit method is a consistent way to estimate (the distribution of) the pre-queue capacity. Indeed, while the queue discharge capacity can only be derived from measurements with upstream congestion, all free-flowing observations do give information about the pre-queue capacity, regardless of whether or not a breakdown follows, in the sense that the momentary pre-queue capacity corresponding to that observation is at least equal to that free-flowing measurement.

The maximum-likelihood method is a parametric estimation method. The parameters of a chosen distribution function are determined such that the (Log-)Likelihood function is maximized (see e.g. Brilon et al., 2005 and Geistefeldt & Brilon, 2009). According to Geistefeldt & Brilon, 2009, an empirical comparison between different function types based on data samples from different German Autobahn sections revealed that freeway capacity is Weibull distributed (Zurlinden 2003; Geistefeldt 2007). Ozbay & Ozguven (2007) comes to the same conclusion. Polus & Pollatschek (2002), however, suggest a shifted gamma distribution.

Finally, the direct breakdown probability method (see Lorenz & Elefteriadou, 2001 and Geistefeldt & Brilon, 2009) defines the pre-queue capacity as a function of breakdown probability. If a threshold breakdown probability is selected, the intensity corresponding to that probability can be considered the capacity. However Geistefeldt & Brilon (2009) states that this method significantly underestimates the breakdown probability at high traffic flows and is thus to be avoided.

Estimation with intensities, speeds and densities

These methods may be helpful if data on intensities, speeds and densities are available, but observations of the capacity state itself are lacking. Two methods are discussed below: the fundamental diagram method (offline) and the related real-time capacity estimation method.

Fundamental diagram:

This method exploits the fundamental relationship between intensity, (harmonic mean) speed and density. An advantage of this method is that it is not absolutely necessary to observe capacity flow. An important drawback of this method is the need for a mathematical model that fits the observed data. Obviously, the resulting capacity depends on the fitting model that is used. Furthermore, the parameters of the chosen model should be calibrated for each site separately and a considerable amount of data is needed (over a broad range of intensities) to allow a reliable fitting (Minderhoud et al., 1997). This approach is used e.g. by Qin & Smith (2001).

Real-time estimation:

This method for real-time traffic predictions and control updates a reference fundamental diagram, determined earlier under predefined conditions. This is done by determining a scaling factor to adapt the pre-defined intensity-occupancy relation2 to the current weather and traffic (composition) conditions. This scaling factor is obtained by comparing predicted and measured intensities. The capacity estimate is derived from the intensity that corresponds with the assumed critical occupancy. This approach is supported by the observation that critical occupancy seems less susceptible to stochastic variations than the capacity (Papageorgiou et al., 2008). According to Minderhoud et al. (1997), often a critical occupancy of 9% is used in this method. Papageorgiou et al. (2008) claim significantly higher values (18-27%). In any case, the critical occupancy is site-specific and dependent on circumstances (although less so than the capacity). Methods to estimate critical occupancy in real-time have been proposed by Smaragdis et al. (2004) en Kosmatopoulos et al. (2006).

5.2.1.3 Indirect-Empirical Methods

If no site-specific data is available, one has to resort to indirect-empirical methods. Firstly, micro-simulation models could be used to estimate the capacity. A notable choice is FOSIM, which has been specifically calibrated to model traffic on Dutch highways. Secondly, some notion about an appropriate capacity value could be obtained from general guidelines given by for example the HCM (Transportation Research Board, 1994) or the Dutch freeway capacity manual ‘Capaciteitswaarde Infrastructuur Autosnelwegen’ (CIA)

[2] According to van Arem & van der Vlist (1992), a quadratic function may be used.

(1999). Capacity estimates for different types of cross sections and using different estimation methods based on two years of empirical data on Dutch highways is presented in Tu et al. (2011).

If available, data from adjacent or nearby sites may be useful to improve the estimate, since Muralidharan et al. (2011) show that capacities are highly correlated across different sections.

5.2.2 Free-flow speed

The free-flow parameter vf is commonly calibrated by performing a least-squares fit on the available flow-density data in uncongested conditions (see e.g. Munoz et al., 2004; Dervisoglu et al., 2009). For instance in Dervisoglu et al. (2009), uncongested condition are identified as the time instants where the speed was reported to be above 55 mph. This is of course dependent on road type, speed limit, etc. Contrary to capacity, the free-flow speed shows negligible variability (Muralidharan et al., 2011) and may thus be modelled as a deterministic value.

5.2.3 Jam Density

The jam density kj and the maximum spillback speed w at a specific location may be determined by a least-squares fit on the congested flow-density data. Therefore, first the critical density kc that corresponds to capacity flow is determined. Munoz et al. (2004) and Dervisoglu et al. (2009) determine kc simply as the intersection point of the capacity and free-flow speed estimated earlier. The data points for which k > kc are then included as congested measurements to fit w and kj. The negative slope of the regression line is w; the point where the regression line crosses zero flow is kj. Often, a constraint is added to ensure that the regression line starts from the capacity, i.e. the tip of the fundamental diagram. Munoz et al. (2004) perform a least-squares fit directly on the data, whereas Dervisoglu et al. (2009) first group all data into non-overlapping density-flow bins (collecting 10 data points each). The data pairs used to fit the regression line are the mean density of a bin paired with the largest non-outlier flow value.

Finally, Muralidharan et al. (2011) note that the variability of the spillback speed w has a relatively insignificant effect on freeway performance compared to variability of capacity. Also, they state that the spillback speed w of a section is virtually uncorrelated with the capacity of the section and with parameters of adjacent sections. We conclude that also the spillback speed w may well be modelled as a deterministic value.

5.2.4 Conclusion

This section discussed the estimation of the parameters of the fundamental diagram to be used in first-order DNL models. It appears that the free-flow speed vf and the jam density kj (and spillback speed w) can be estimated with a least-square fitting on the uncongested and congested flow-density data respectively. Of course, this implies that sufficient data should be available. Since the variability of these parameters is found to be very low (for vf) or negligible compared to variability of the capacity (for w and kj), these parameters may be modelled as deterministic values. Also, it seems justified to adopt estimates for these parameters from adjacent sections or time periods, should data for a specific location and time be missing; particularly for the free-flow speed vf.

Reliable estimation of the capacity C is significantly more troublesome. Table 4 summarizes the findings of Minderhoud et al. (1997). We should add to this that Minderhoud et al. (1997) explicitly state that no method is satisfactorily reliable.

Table 4: Characteristics of various capacity estimation methods (Minderhoud et al., 1997)

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Section	*Method:*	*Data needs:*				*Traffic State[a]:*		*Capacity:*		*Type[b]:*	*Validity:*
		h	q	v	k	{Q}	{C}	q_c	F(q)		(- -, -, o, +, ++)
4-1	Headway Models	Yes				Yes		Yes		1	-
4-2-1	Bimodal Distr.		Yes			Yes	Yes		Yes	m	o
4-2-2	Selected Maxima		Yes			Yes	Yes		Yes	m	o
4-2-3	Direct Probability		Yes				Yes	Yes		d	-
4-2-3	Asymptotic		Yes				Yes	Yes		d	- -
4-3-1	Empirical Distr.		Yes	Yes			Yes		Yes	2	+
4-3-1	Product Limit		Yes	Yes		Yes	Yes		Yes	m	++
4-3-1	Selection		Yes	Yes		Yes	Yes	Yes		m	-
4-4-1	Fundamental Dgrm.		Yes	(Yes)	Yes	Yes		Yes		d	+
4-4-2	On-Line Procedure		Yes	Yes	Yes	Yes		Yes		1	o

[a] {Q} represents free flow intensities, {C} represents congested flow intensities (under the condition of a congested traffic state upstream leading to *maximum* congested flow intensities).

[b] type 1 denotes a capacity value estimation representing the maximum free flow intensity, type 2 denotes a capacity value estimation representing the maximum congested flow intensity, *m* stands for type 1 and 2 mixed into one capacity estimate and *d* stands for the dependency with the study set up (either type 1 or 2 is possible).

The choice of an appropriate capacity estimation method is largely determined by data availability. Furthermore, the type of capacity – pre-queue or queue discharge – one wishes to estimate influences this choice. Assuming data on intensities and speeds are available, the empirical distribution method is recommended for estimating queue discharge capacity and the product limit method as defined in Geistefeldt & Brilon (2009) and the Maximum-Likelihood method3 suit pre-queue capacity estimation (Minderhoud et al., 1997; Hoogendoorn & van Lint, 2006). The type of application is decisive for the choice of whether to implement pre-queue or queue discharge capacity in the DNL model. A pre-queue capacity is preferable if the modeling of the maximum possible traffic flow is needed, for example in case of ramp metering (traffic flow should not be larger than the given pre-queue capacity). Queue-discharge capacity on the other hand may be used for delay estimation at bottlenecks (Tu et al., 2010).

Notably, Table 4 also indicates which methods provide a single, deterministic capacity estimate and which ones produce capacity distributions. Considering the stochastic nature of capacity and the relatively significant impact its variability has on the traffic conditions, the latter is to be preferred. Probabilistic distributions of capacity provide a far more complete picture than one deterministic value. Moreover, Muralidharan et al. (2011) state that the capacity distribution of the entire freeway needs to be modelled as a multidimensional joint distribution, since they found a strong correlation between the capacities of adjacent section.4 This also implies that capacities for sections where data is lacking could be derived from the joint capacity distribution model.

[3] Geistefeldt & Brilon (2009) find that the product limit method and the Maximum-Likelihood technique always lead to a rather good coincidence of the estimated capacity distribution functions.

[4] They excluded data points in sections that were observed either as a result of congestion spillback or obvious lack of demand.

From a capacity distribution, an appropriate capacity value may be selected based on additional information on momentary circumstances (e.g. regarding weather or fleet composition) to model specific conditions. In absence of such information, determining a deterministic capacity value is difficult. The specific application may influence this choice, for instance: is a worst-case or rather a best-case scenario aimed for? In general, Tu et al. (2010) advise to use the median value to avoid the influence of outliers (which may strongly affect the mean value) – this seems to be supported by Minderhoud et al. (1997) as well.

Finally, it should be noted that the results of any capacity estimation are significantly influenced by the choice of the data aggregation interval. Tu et al. (2010) show for instance that the capacity differences resulting from 5 min and 15 min aggregation intervals vary from 0% and 23% with a mean value of 5% and a standard deviation of 3.3%. Most studies seem to choose either 5 or 15 min without a proper motivation. The HCM (Transportation Research Board, 1994) considers 15 min to be the interval during which stable flow exists. Qin & Smith (2001) claim that a study of Smith (2001)5 found that stable capacities may be calculated from aggregation intervals of 10 min. However, adding 2 min to any aggregation interval is stated to statistically significantly improve the stability. In conclusion, it seems unadvisable to adopt very short aggregation intervals such as 5 min.

5.3 Ramp Demands and Split Rates

The demands from on-ramps and the split rates towards off-ramps are boundary conditions to the freeway network. Predictions of these inputs can be made for instance by time series using both historical profiles and real-time data (Section 5.2.1). Ideally, this data is obtained from flow measurements on the ramps themselves. Temporal unavailability of data due to malfunctioning detectors may be solved by interpolation techniques (see Boyles, 2011 for an overview). For unmeasured ramps (without detectors), this data is permanently unavailable.

Section 5.3.2 highlights some existing methods to derive this data from other detector measurements and/or local characteristics.

5.3.1 Time Series Prediction

To come up with traffic state prediction, predictions of the boundary conditions of the network are needed. Ramp flows expected in the future need to be forecasted during the prediction horizon. More specifically, for the first-order traffic flow prediction model used in this project, the demands at on-ramps and the split rates at off-ramps need to be predicted. Time series prediction methods seem appropriate for this due to their relative simplicity and low computational effort. Preferably, information on historical flow profiles is used, as well as recent (e.g. the last 30 min) flow measurements. Of course, if flow measurements are lacking, one can use only historical or whatever information that is available; see the next section for some options to estimate flows at unmeasured locations.

Several studies in the state-of-the-art apply time series to predict traffic variables (mostly speeds, flows and/or travel times), using both historical and real-time information. Some of the more recent that aim to predict traffic flows are the following. Min & Wynter (2011) apply a multivariate spatial-temporal autoregressive model (VARMA). Zhang et al. (2011) propose a hybrid methodology combining the linear SARIMA model and non-linear Support Vector Machines Regression. More details and references on time series prediction models were presented in Section 1.2.2.2.

In the remainder, we elaborate in more detail on the approach of RENAISSANCE (Wang et al., 2004), which specifically aims to predict the network boundary conditions such as on-ramp inflows and off-ramp split rates. See also Tampère et al. (2009) for more details.

[5] Qin & Smith (2001) fail to provide a reference for the Smith (2001) study. We were unable to find it ourselves.

The future boundary conditions (over a user-defined prediction time horizon) can be predicted from smoothed historical profiles, a trend extrapolation of recent estimates (obtained from an extended Kalman Filter state estimator) or by a combination of these two. In the combined approach, the prediction for a near-future time instants will rely more heavily on the recent estimates, while further away predictions tend more towards the historical profile. Trend extrapolation and the possible combination with historical profiles are discussed below.

5.3.1.1 The Trend Extrapolation

First, for each boundary condition (e.g. a ramp flow or split rate) a linear function is fitted – using standard regression formula - through the N most recent estimates $\hat{d}(\kappa)$:

$$\begin{aligned} &d^F(\kappa) = a^F + b^F(k-\kappa) \\ &with: \\ &\kappa = k, k-1, \ldots, k-N \end{aligned} \tag{0.3}$$

In (0.3), k is the current estimation time step where the prediction starts from. A trend extrapolation Kp time steps into the future is done with the obtained fitting parameters:

$$\begin{aligned} &d^E(\kappa) = a^E + b^F\varepsilon(k-\kappa) \\ &with: \\ &\kappa = k, k+1, \ldots, k+K_p \end{aligned} \tag{0.4}$$

The trend compliance parameter $\varepsilon \in [0,1]$ is user-defined. For a^E (the starting point of the extrapolation), there are two options:

$a^E = \hat{d}(k)$, i.e. the first value $d^E(k)$ in the extrapolation is equal to the most recent estimate (only the fitted b^F parameter is used in this case)

Or $a^E = a^F$, i.e. both fitting parameters a^F and b^F are used and the first value in the extrapolation is $d^E(k) = a^F$,

Predictions based on extrapolation only are, by construction, straight lines.

5.3.1.2 Combination With Historical Profiles

The following options exist in RENAISSANCE for combining the historical value $d^h(\kappa)$ with the trend extrapolation $d^E(\kappa)$ into a prediction value $d^p(\kappa)$ for a future time step κ:

No historical profiles are used, only trend extrapolation as described above. The predicted value $d^p(\kappa) = d^E(\kappa)$.

A weighted sum of the extrapolated value and the historical value is made, using constant weights.

A transition between trend extrapolation and the historical profile is performed. The weights of the historical value and the trend extrapolation linearly increase (decrease) from 0 (1) at time step *k* to 1 (0) at the end of the fade over period.

The historical profile is used in its entirety, but it is shifted so that the starting point coincides with the starting point of the trend extrapolation:

$$
\begin{aligned}
& d^{p}(\kappa) = d^{E}(k) + \Delta d^{h}(\kappa) \\
& with: \\
& \kappa = k, k+1, \ldots, k+K_{p} \\
& \Delta d^{h}(\kappa) = d^{h}(\kappa) - d^{h}(k)
\end{aligned} \tag{0.5}
$$

In Tampère et al. (2009), N in (0.3) was chosen (after some rough calibration) so that estimates from the last 30 minutes were taken into account. This was found to be a good compromise between the smoothing of low-significance high-frequency “noise” and a relatively fast identification of significant trend changes (e.g. at the start of the peak period). For similar reasons, the trend compliance ε was set to 0.5. Only for split rates, $\varepsilon = 0$ was used. This implies the assumption of constant split rates over the prediction horizon, which is reasonable given the fact that split rates are usually quite stable. When using historical data in combination with extrapolation for the boundary variable prediction, the third option described above was used, with a transition period of 30 min (i.e., equal to the prediction horizon). Hence, combined predictions are (generally) nonlinear curves starting at the current estimate and ending at the respective historical value. Finally, in Tampère et al. (2009), an upper bound for the predicted value of the boundary variables was generally set to the maximum observed value of that variable, increased by 10-15%. The reason for this is to exclude unrealistic predictions due to exaggerated trends.

It is concluded in Tampère et al. (2009) that, while all predictions are fairly reasonable, predictions combining historical data and trend extrapolation of recent estimates are generally slightly better.

5.3.2 Unmeasured Locations

In the following, we are concerned with deriving information on unmeasured ramp flows. In the future, floating car data may provide a solution on ramps without permanent detectors. Currently, however, floating car data are not available for this project.

The problem of estimating missing ramp flow data may range from quite trivial to highly challenging. The former applies to situations where flow measurements on the freeway are available before the off-ramp, after the on-ramp and in between the two. Provided the absence of congestion, the missing data can be easily retrieved based on conservation of vehicles throughout the freeway complex. Congestion on the ramps or a non-negligible spatial distance between freeway detectors may render the derivation of this relationship more troublesome. An estimation method that may be helpful in such cases is presented by Muralidharan et al. (2009). This is described in Section 2.2.1. If also flow measurements on the freeway are incomplete, accurate estimation of ramp flows becomes difficult. Section 2.2.2 highlights some studies that estimate annually average daily traffic counts using various techniques such as standard regression techniques, geographic weighted regression and geostatistical methods. Also, a method based on static assignment is included.

5.3.2.1 Ramp Flow Estimation With Full Availability Of Freeway Measurements

Muralidharan et al. (2009) provide an automated procedure to determine missing ramp flow measurements. This method uses an adaptive identification techniques adopted from iterative learning control (Messner et al., 1991 and Horowitz et al., 1991) which minimizes the error between measured and simulated densities at freeway detector locations. The simulation model used is the Aurora Link-Node Cell Transmission Model (LN-CTM), see Kurzhanskiy (2007) and Muralidharan et al. (2009) for details.

The estimation procedure in Muralidharan et al. (2009) is an iterative process, in which the on-ramp demand and off-ramp split rate estimates are updated with each run of the LN-CTM until the error between measured and simulated densities is sufficiently small or converges. The update functions that are used to determine ramp demands and split rates depend on the traffic regimes upstream and downstream (free flow or congestion).

This method assumes that detectors are available in each freeway sections providing the density measurements. Also in the section between off-ramps and on-ramps a detector location is required to conclusively determine the off-ramp split rates and on-ramp demands. Not surprisingly, this allows estimating these variables with high accuracy, as shown by a case study on a 26 mile portion of the I210E freeway in California. The next section discusses methods that may be used when detector locations are scarcer.

5.3.2.2 Ramp Flow Estimation With Incomplete Availability Of Freeway Measurements

Furthermore, another field of literature was found that uses standard regression techniques, geographic weighted regression and geostatistical methods to estimate annually average daily traffic counts (AADT) (veh/day). Although, in order to be useful for prediction modeling, a dynamic profile would have to be derived from these AADT – that would still only represent average conditions – a brief introduction on this literature may enrich our expertise.

The following very briefly summarizes the overview in Selby & Kockelman (2011). Each mentioned method takes known counts at available detector locations and uses additional information (e.g. local land use and road characteristics) to make an estimate for unmeasured locations. These can be divided into future-year (or future-period) estimation and same-year estimation methods. This discussion is limited to the latter.

Zhao and Chung (2001) use local information on employment, population and road characteristics to estimate AADT in a least-squares regression. They found that number of lanes, road function, regional access to employment, employment in an adjacent buffer zone, and direct access to expressways have the largest explanatory value. Zhao and Park (2004) performed a similar study, replacing the least-squares with a geographically weighted regression, which calculates local parameters from a distance-based weighting function. This specification clearly outperformed the least-squares method on the same data. Wang and Kockelman (2009) used ordinary kriging, which is a geostatistical method that estimates an unknown global mean value as well as the spatial correlation with nearby data points. However, ordinary kriging does not allow accounting for location-specific characteristics. According to Selby & Kockelman (2011), this leads to significant errors. Eom et al. (2006) use universal kriging, which does not assume a global mean and combines the distance-based variance with a trend, such as a linear, parametric function. Universal kriging makes use of both spatial and local information. Their results suggest that universal kriging improved the estimation results. This is confirmed by the case study in Selby & Kockelman (2011), which is briefly described below.

The estimated AADT (veh/day) (in matrix Z) are obtained from the following problem formulation (Selby & Kockelman, 2011):

$$Z = X\beta + \varepsilon \tag{0.6}$$

Therein, X is the data matrix, β are linear parameters and ε is the error term, which is defined as a function of the distances between the locations of data points. Selby & Kockelman (2011) use speed limit, number of lanes, road type, and population and employment densities as data variables. The β parameters and the parameters in the error function ε are estimated via a weighted least-squares regression using the AADT at measured locations. Then, using these values, estimations for the AADT at unmeasured locations can be made. Selby & Kockelman (2011) present a case study for the state of Texas, USA. The available detector locations are rather sparse (about 0.2 locations per square mile). Their results show a large average absolute error of about 60% between estimated and measured counts for the validation data set. However, the results on the interstates are significantly better (20% average absolute error). They show that their results are a significant improvement over non-spatial regression techniques.

Surprisingly, they found that using network distances in the error term functions provides no significant improvement over using Euclidean distances, which are much easier to calculate.

5.3.3 Conclusion

Regarding the prediction of boundary flow and split rate values at measured locations, the use of time series seems advisable for reasons of simplicity and computation time. The RENAISSANCE approach has been thoroughly described.

At unmeasured locations, both historical and real-time data from detectors is missing. In this case, an estimation of the flow profiles has to be performed. Likely, only a rough estimation with quite high errors will be possible. Firstly, the approach of Muralidharan (2009) has been highlighted, which may be interesting since it is automated and its estimates depend on the traffic states, instead of simply assuming free flow conditions to always hold. Secondly, some (geo)statistical literature to estimate Annual Average Daily Traffic (AADT) volumes has been described.

Typically, these studies aim to produce one average value, but the same techniques could be applied to estimate seasonal or day-of-week traffic volumes. Before use in a traffic flow prediction model, these AADT would first have to be disaggregated to dynamic flows varying within-day. Although the reported accuracy of the mentioned studies is already quite low for these daily averages, still this overview may be useful to add to our expertise and for FileRadar to improve on their current ad-hoc methodology to estimate flows and split rates at unmeasured locations.

5.4 Alternatives to Extended Kalman-Filtering for State Estimation

5.4.1 Problem Analysis

In online traffic flow propagation methods, a crucial step is the combination of on the one hand the prior estimate (i.e. the model prediction that incorporates all previous measurement information and the system dynamics) and on the other hand the actual measurement data. This problem is known in literature as 'state estimation', 'statistical estimation' or 'data assimilation'.

Just like many of the online traffic simulators of section 2.3.1, the FileRadar application used in this project is based on Kalman filter theory. This theory assumes the state variable estimates and noises (both system and measurement noise) to be normally distributed, and the system model to be linear. Under those conditions, Kalman filter is one of the simplest algorithms for recursive Bayesian estimation, guaranteeing optimality for the posterior estimate.

There are several difficulties involved when applying Kalman filtering on a large traffic network in a real-time setting with a cell transmission traffic (CTM) flow model:

CTM is not a linear system model. Rather it is a piecewise linear model. As a consequence, the model needs to be linearized at every time step, yielding an extended Kalman filter (Tampère & Immers, 2007). EKF intrinsically means that one loses the optimality property of the linear Kalman filter and the state estimation becomes heuristic.

A large traffic network requires many state variables in the CTM. As a consequence the matrix-based EKF procedure in principle involves inversion of prohibitively large (be it sparse) matrices.

The consequence of the non-linearity of the system model is serious, as Figure 6 illustrates. As one is uncertain about the state (e.g. density k), the linear approximate system model may be different dependent on k (in this example: piecewise linear with different slope depending on k, i.e. the system state k will be transformed radically different, depending on the linear regime it belongs to). Hence, the unimodal probability distribution of k may easily break up into multimodal distributions, as the figure illustrates. Yet, EKF will keep on approximating this pdf as a Gaussian distribution. As the figure illustrates, this problem would typically occur when the system state is close to capacity (the switching point between two linear regimes). This may cause the filter to diverge, exactly in traffic conditions that are of particular interest, as near-capacity traffic is prone to breakdown to congestion, which is exactly when predictions would be ultimately useful.

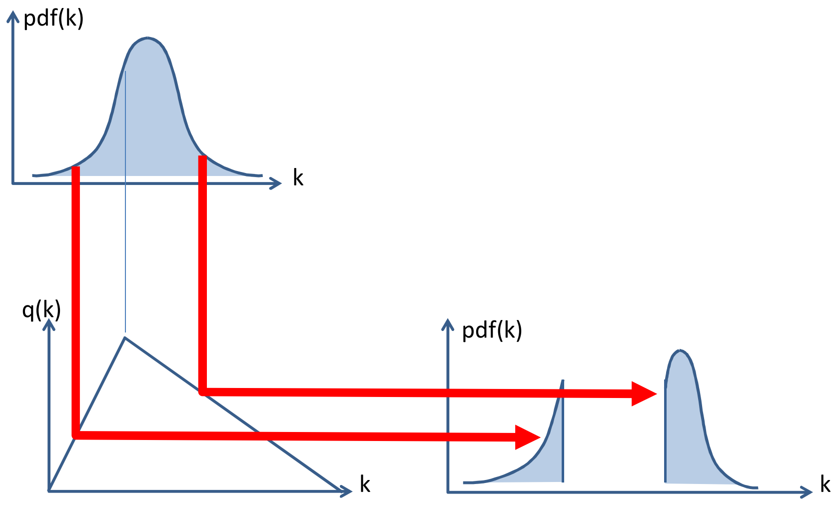


Figure 6: Non-linearity and non-Gaussian state estimates

If this is the case and one is going to neglect this non-Gaussian propagation of uncertainty in the system model anyway, one may wonder whether it is worth spending much calculatory effort in computing a theoretically elegant recursive filter like EKF with its associate cumbersome matrix inversion.

The remainder of this section considers two possible approaches to this problem: either one turns to theoretically more powerful reclusive state estimators that can deal with non-linearity and arbitrary probability distributions of the state variables, or one turns to more pragmatic heuristics that are computationally less expensive than EKF.

5.4.2 Non-linear, non-Gaussian filtering

There are many theoretically more advanced filters than EKF that are not limited by assumptions on the error distributions or system/measurement models. The most common ones are:

- Fast Kalman filter (FKF)
- Gaussian sum filter
- Unscented Kalman filter (UKF)
- Particle filter (PF)

The Fast Kalman filter (Lange, 1996) is a patented procedure that exploits the sparse, quasi-diagonal form of the matrices that need to be inverted to compute the Kalman gain matrix. This is claimed to accelerate real-time deployment on large control systems significantly.

UKF and PF are based on the same idea: the pdf of the true state vector is discretized by a limited number of state vectors and their corresponding probabilities; these vectors are non-linearly transformed to yield a prior pdf of the state, after which the measurements are used to make a Bayesian posterior pdf. The difference between UKF and PF lies in the discretization of the pdf. In UKF, so-called sigma points are selected: a specific way of sampling aimed at producing the same mean and covariance as the true state vector. In PF, a random sample out of the pdf is taken, which is typically larger than the UKF sample but can represent any arbitrary pdf closer than the sigma points of the UKF. Examples of application of UKF to online traffic simulation can be found in (Mihaylova et al. 2006; R. Pueboobpaphan & T. Nakatsuji 2006; Rattaphol Pueboobpaphan et al. 2007; Ngoduy 2011). Examples of particle filters to traffic state estimation are due to (Mihaylova & Boel 2004; Peng Cheng et al. 2006). The concept of the Gaussian sum filter is closely related. However, rather than sampling, the non-Gaussian distribution is decomposed as a sum of Gaussians. The (E)KF can then be applied to each of these components after which they are recombined into an estimate of the original pdf.

The drawback of any of these non-linear solutions is that they require more computational power (e.g. the PF is commonly referred to as a 'brute power' approach). Certainly in large networks, the number of state variables and hence of samples may become prohibitively large. For that reason, we no further elaborate them in this report and refer the reader to specialized literature such as Simon (2006) and the authors already mentioned.

5.4.3 Pragmatic Data Assimilation

In this section, a limited number of pragmatic approaches to data assimilation is reported. These approaches are not formulated as recursive Bayesian estimators. However the structure of the procedure sometimes mimics the essence of such estimators, in that a prior state estimation, which accounts for all measurement so far as propagated by the system model, is combined with a new approximate state observation, albeit now in a heuristic rather than (quasi-)optimal way.

Barlovic et al. (1999) describe an online traffic simulation model for Duisburg based on cellular automata. They correct the traffic states by considering artificial sources and sinks at detector station locations, through which they add or remove vehicles to compensate for the difference between modeled and observed traffic. As such, they do not really apply data assimilation, they rather locally replace simulated by observed traffic state, assuming perfect measurements. They justify their approach, stating that the model inevitably contains errors because in an urban environment vehicles may enter or leave the network anywhere (e.g. through parallel parking); hence the model is by far less reliable than measured data.

Schreiter et al. (2011) initialize an online traffic flow prediction model by a traffic state estimation based on Adaptive Smoothing filtering (Schreiter et al., 2010). That filter does not consider any online traffic flow model. Rather, it smoothens and interpolates traffic states along all links, based on past measurements at detector stations and through traffic flow theoretical principles. Hence, the traffic state predicted in previous time intervals is not taken into account; rather the online traffic model is reinitiated at every measurement update time interval based purely on all relevant available data.

Vortisch (2006) describes a pragmatic approach for real-time traffic state estimation in urban networks. The procedure is conceptually related to that of Schreiter, however, rather than applying traffic flow theoretical principles to propagate measured information, Vortisch uses split-rates and route fractions as a basis for extrapolating local flow measurements to neighbouring links in the network. The route fractions are obtained from an offline static planning model, or might be retrieved from online data sources like floating car data. As links are further away from a detector (in terms of number of intermediate nodes), the uncertainty of the extrapolation grows. On the other hand, multiple flow estimates are obtained for each link, based on extrapolation from multiple detectors. Vortisch (2006) mixes these estimates weighed with their respective degree of certainty, the latter being quantified in a heuristic way as an exponential decay. Even though the author does not suggest this, it is relatively straightforward to propose an extension where also previous estimates for the same link are taken into account as additional estimations to be appropriately weighted. Following the philosophy of the paper, the certainty of such past estimates might be approximated by an exponential decay in time (e.g. (double) exponential smoothing). By doing so, the procedure would resemble an oversimplified version of the weighting done in recursive Bayesian filters. Finally, Vortisch (2006) proposes a set of corrections to his basic procedure in order to account for capacity constraints and queue spillback.

6 Review of Selected Applications

6.1 Introduction

The following section provides a review of the applications that were selected within this Work Package. In addition to describing the location specifics, we describe the objectives of the system, the software that has been used, the collected data, whether or not the generation of multiple scenarios has been used, and which open issues were identified. There is also a brief overview of other potential cases that were found, although there is no much literature available.

6.2 Case: Berlin

City/Country:	▪ ***Berlin / Germany***
Organization:	▪ Berlin Traffic Management Center (TMC) (or VMZ Berlin Betreibergesellschaft in German). This institution is divided in two departments: - Business to Administration division (B2A): focuses on providing services to the public sector by assisting local and federal authorities in the development and implementation of future-oriented traffic management concepts. - Business to Business division (B2B): is geared towards companies from a variety of industries. ▪ The free traffic information services of VMZ are made possible by a new type of cooperation between public and private partners. The initial investment costs for the setup of VMZ were financed by the Senate Department for Urban Development of Berlin, whilst VMZ is responsible for the continued operation and further development of the traffic management system.
Type of network, size:	▪ Urban network - the city of Berlin (891.85 km2).
Time line:	▪ Trial period: date unknown. ▪ It is currently operational.
Objectives:	▪ To provide information: Monitoring and improving mobility by providing free of charge traffic information to the State of Berlin and the general public.
Software:	▪ VISUM Online: traffic planning software developed by PTV in Germany. ▪ The software is used to estimate the overall traffic state and to calculate a short-term forecast with a time horizon of 30 minutes. ▪ During the trials three demand matrices were available from traffic planning, one for the morning peak hours (6:00 to 9:00), one for the afternoon peak hours (15:00 to 17:00), and one for the rest of the day. All matrices referred to normal work days, i.e. no further distinction was made for weekdays. ▪ No further information found on current demand matrices.
Scenario generation:	▪ Project focuses on providing information and not on developing control strategies. Hence, only a single prediction (based on current state) is made.
Data collection:	▪ Approximately 250 detectors have been installed in Berlin for traffic monitoring. They are all autonomous overhead detectors supplied by solar power and transmitting the measured values to the control center by mobile radio (so-called Traffic Eyes developed by Siemens). Traffic volume and mean speed are acquired in 5-minute intervals. However, transmission to the control center is only triggered when the acquired parameters undergo major changes. ▪ The dedicated detectors are complemented by inductive loop detectors on some motorway sections of Berlin on which section control systems are being operated. Particularly the southern part of the motorway ring-road is covered completely by inductive loops, adding up to more than 150. However they are not equally distributed across the network. ▪ Data from the public transport systems (BVG, S-Bahn Berlin GmbH, and VBB), or even individual callers reporting specific situations/conditions. ▪ 20 webcams. ▪ Floating car data (FCD) from buses and taxis. Information about the travel speed on individual links of the network model is provided by these two sources. As the data is collected in periods of 15 minutes in order to forecast the following 15 minutes in the same link, the covering of the network with this kind of information is temporally variable, depending on the availability of FCD.

Interventions:	▪ All messages to be provided to the public, based on either the information received or the predictions made by the system, are available to the editor. He is supported by an automatic detection of contradictory information, to ensure that all the outgoing messages are consistent. ▪ The users can get varied information from the website (www.vmzberlin.de). This includes congestion problems, construction sites, current parking situation, traffic forecasts, or traffic conditions via web cams. They can also use the inter-modal dynamic route finder to plan journeys based on up-to-the-minute traffic information and different transport modes. ▪ Dynamic roadside information panels are used to inform the drivers of the traffic conditions ahead. ▪ Every half an hour Radio Berlin 88.8 broadcasts the current traffic situation directly from the TMC.
Open Issues:	▪ The allocation of attributes (e.g., speed, flow) to the road network provided by traffic planning turned out to be rather problematic. There were various network variants for the different times of the day to model the time-dependent utilization of bus lanes, but there was no explicit or implicit modeling of different intersection capacities due to traffic signal programs changing over the day. ▪ The field trials revealed that situations may arise for which the traffic volume approaching an intersection can be estimated fairly accurately, but the resulting level of service could not be determined correctly because the intersection capacity was not really known
Other:	▪ A field test during which an independent traffic expert compared additional measurements in the road network with the estimated results was carried out. The test was successful according to the criteria applied. ▪ However, only a relatively small sample of places and times were verified during this test due to the large effort required for the additional measurements. Therefore, a statistically significant proof of the accuracy of the model has not been provided yet. In spite of that, the system has been operative for a while, with the traffic editor being the system observer. ▪ More than half of the critical cases during the first year of operation were due to errors of system technology: - The editor observed inconsistencies between the measured values and the calculated traffic states, when using both as inputs for the next iteration of the estimating system. - The location of information in the road network during the estimation process was a typical source of problems because the original models used different geographical reference systems. ▪ There were also initial errors in the calculation method: - The traffic editor observed implausible behavior of the calculation e.g. no congestion at sites at which either an incident had been detected or a traffic message concerning impedance had been entered into the system. ▪ Chart below shows the architecture of the model:

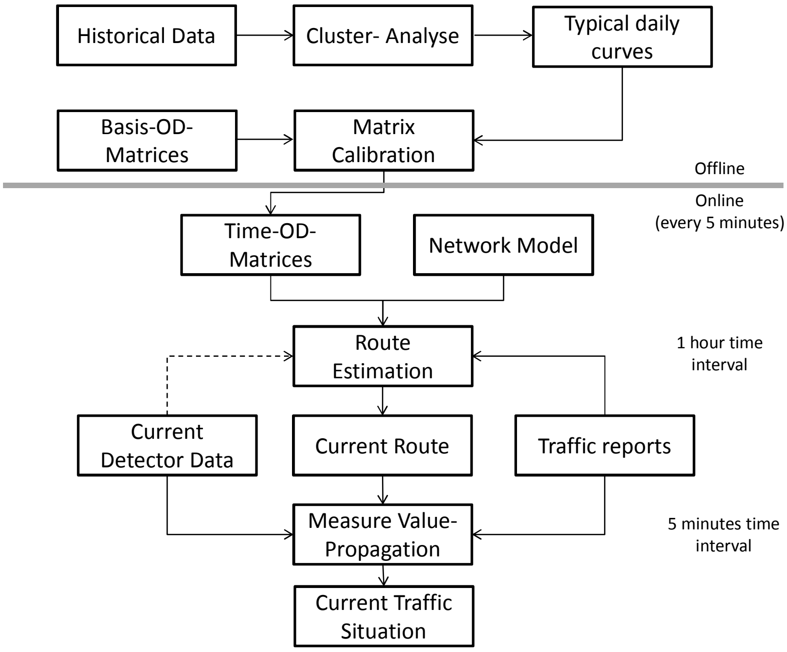


Figure 7 Architecture of the Berlin model. Source: Vortisch (2006) – translated by ETH Zürich.

References:

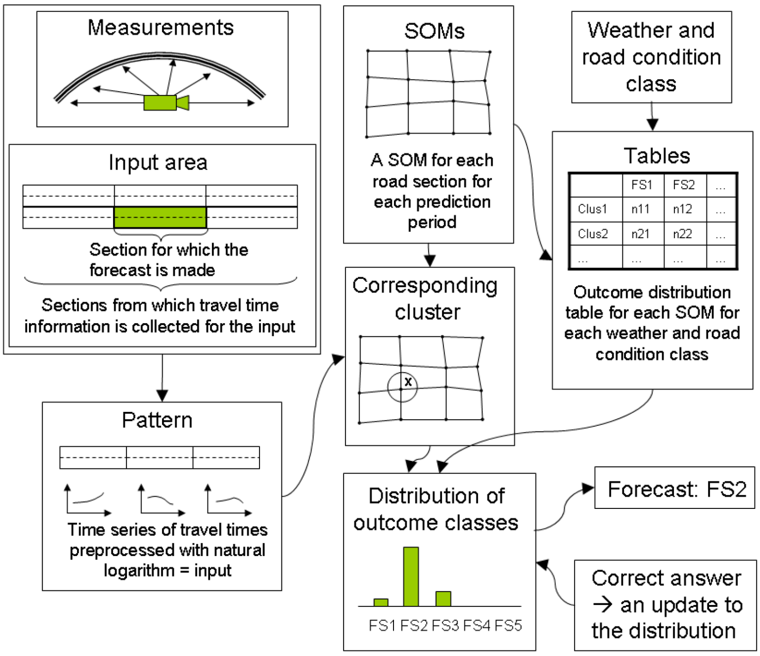
- Vortisch, P. (2006) Model-Supported Propagation of Measured Values for Real-Time Traffic State Estimation in Urban Road Networks, PTV AG, Karlsruhe.

6.3 Case: Dusseldorf

City/Country:	▪ ***Düsseldorf / Germany***
Organization:	▪ Department for Traffic Management.
Type of network, size:	▪ Urban network - The city of Düsseldorf (217 km2). It is divided in 29,000 links, 560 zones and 2 million of OD components.
Time line:	▪ Currently operational, although no forecasts are given to the public.
Objectives:	▪ To provide information: Estimating and predicting future traffic states (including travel times). ▪ Control and management of the traffic system.
Software:	▪ The Dusseldorf Traffic Management Center is currently using PTV Traffic Platform, a product developed by PTV in Germany for traffic modeling and prediction. ▪ PTV Traffic Platform is an ITS platform for traffic monitoring and management developed by PTV in Germany. In the future PTV Traffic Platform will be replaced by the PTV product OPTIMA. - It produces off-line estimations, real-time flow, and travel time prediction. - It produces a traffic estimation during each day-type. - The product was especially conceived for metropolitan areas because the congestion is stronger, but it can also be applied in non-urban areas. - Every 10 minutes it produces 1 hour simulation, including 5 complete network state forecasts (with 10, 20, 30, 40 and 50 minutes time horizons). - Predicted traffic states consist of inflows, outflows, travel times, vehicular densities, and queues on every link of the network. - The software responds to events that are automatically inserted. It also reacts to modified characteristics of the network (e.g. adding bottlenecks, changing cycle times of traffic lights, closing streets).
Scenario generation:	▪ The operator can simulate in real-time the effects of an event, accidental or generated as a control measure, by clicking into the link and inserting the type of event (already predefined).
Data collection:	▪ 560 loop detectors, which provide flows and in some cases speeds every minute. ▪ Signal information (e.g., green time splits). ▪ Incident information, generated by their own grid, or from third party systems.
Interventions:	▪ There is currently a website (http://www.duesseldorf.de/vid/) offering information to the public, although just real-time information, and not forecast information. ▪ Nevertheless, the prediction algorithms are being implemented already, but at this point the results are only available to the Department of Traffic Management, and not to the general public. ▪ It is worth noticing that even the real-time information presented in the website proceeds from a 10-minute prediction model (to account for data collection, computing, and displaying time).
Open Issues:	▪ No information has been found.
References:	▪ Gentile, G., L. Meschini (2011) Using dynamic assignment models for real-time traffic forecast on large urban networks, Proceedings for the 2nd International Conference on Models and Technologies for Intelligent Transportation Systems, Leuven, Belgium. ▪ Möhl, P. (2011) Use cases of Intelligent Traffic Management, Presentation for PTV Traffic Mobility Logistics. ▪ Möhl, P. (2011) Yellowhead Trail ITS Simulation Laboratory and Edmonton Showcasel, Presentation for PTV Traffic Mobility Logistics.

6.4 Case: Helsinki

City/Country:	▪ ***Helsinki / Finland***
Organization:	▪ Project carried out by VTT Technical Research Centre of Finland, and funded by: - Ministry of Transport and Communications. - Finnish Road Administration. ▪ The study was part of the Finnish Research and Development Program on ITS Infrastructures and Services (FITS) 2001-2004.
Type of network, size:	▪ Motorway - Ring Road I in the Helsinki Metropolitan Area. This road was usually congested during morning and evening peak hours on working days. The annual average daily traffic volume used to be around 85.000 vehicles and the highest daily traffic volumes exceeded 100.000 vehicles. For the busiest 100 hours of the year the traffic volume in the middle part of the road exceeded 9.600 vehicles per hour, and 6.000 vehicles per hour in the western and eastern parts of the road. ▪ The trial started from the western part of the ring with 2 lanes in each direction. However, in some sections there were 3 lanes in each direction (from the Otaniemi junction to the main road 110, and from the main road 120 to the main road 45). The road had an alternating bus lane in addition to the 2 lanes per direction east of the main road 4.
Time line:	▪ Models were based on data collected during an 8-month period from January to August 2004. ▪ The prediction performance of the models was tested during a 250-day period starting in January 2005
Objectives:	▪ To provide information: Predicting future traffic flows based on current traffic flows, weather and road conditions.
Software:	▪ SOM is a Self-Organising Map. An unsupervised neural network method useful when the classification of the data is unknown or when the use of this classification is not desired. ▪ A SOM consists of neurons (processing units or map units) organized on a regular low-dimensional grid. Distances between the map units are measured with the distance of their weight vectors in grid coordinates. ▪ Besides the processing of the input and the updating procedure, the model only needs to determine Euclidian distances to the map units and the most common outcome of the distribution table of the map unit with the minimum distance. ▪ Even though making a SOM requires some computational power, once it is ready, for running the model there are not any special requirements. ▪ The outcome of the model defines the traffic flow status class of the road section. Five traffic flow status classes are determined according to the ratio of measured speeds to free-flow speeds: - Free-flowing traffic > 90 % - Heavy traffic 75-90 % - Slow traffic 25-75 % - Queuing traffic 10-25 % - Stopped traffic < 10 % ▪ Traffic conditions are classified as congested if the flow status class is slow, queuing or stopped. ▪ Forecasts were made with a time horizon of 15 minutes on the basis of weather, road conditions, and travel time information. ▪ The forecasts were given at 5 minute intervals for 5 minute periods, e.g. separately for vehicles entering the sections in the periods 0-5 min, 5-10 min, and 10-15 min. ▪ The model was divided into sub-models according to the weather and road condition class (normal, poor, hazardous). ▪ The effects of weather and road conditions on forecasts were investigated by

	comparing the performance of the model with and without these inputs. The results showed that the average performance of the model was similar for both normal and hazardous weather and road conditions.
Scenario generation:	▪ Project focuses on providing information and not on developing control strategies. Hence, only a single prediction (based on current state) is made.
Data collection:	▪ Six camera stations.
Interventions:	▪ No information has been found.
Open Issues:	▪ The model has problems in reacting when a change in traffic patterns appears. Hence, it is better to reinitialize the outcome tables and restart the data collection if there are considerable changes in the traffic management or in the road network. ▪ During the weekends most of the predictions are incorrect due to the low quantity of observations of congested traffic.
Other:	▪ Storage of all the samples of traffic situations is not required (an advantage of this model compared to others). In this study, storing all the samples would have led to a database of 62 million items in 5 years. By using the condensed version of the same history, only 10 tables of fixed size of at most 14.000 items are stored. ▪ Chart below shows a schematic representation of the basic architecture of the model.  **Figure 8 Architecture of the Helsinki model. Source: Innamaa (2009).**
References:	▪ Innamaa, S. (2009) Short-term prediction of traffic flow status for online driver information, PhD dissertation, Helsinki University. ▪ Innamaa, S. (2010) Self-adapting prediction model for traffic flow status, proceedings for 12th WCTR, Lisbon, Portugal.

6.5 Case: London

<table>
<tr><td>City/Country:</td><td>London / United Kingdom</td></tr>
<tr><td>Organization:</td><td>Program supported by Transport for London and the Directorate of Traffic Management</td></tr>
<tr><td>Type of network, size:</td><td>Urban network – City of Westminster, South west London borough (21,5 km2).</td></tr>
<tr><td>Time line:</td><td>Currently in testing phase. Multiple companies (PTV, TSS and IBM) are conducting trials, testing their specific software, in an area of London.</td></tr>
<tr><td>Objectives:</td><td>To provide information: Estimating and predicting future traffic states (including travel times).
Control and management of the traffic system.</td></tr>
<tr><td>Software:</td><td>PTV, TSS and IBM are all testing their specific software. This review will focus on the PTV trial, with the software OPTIMA.
OPTIMA is an ITS platform for traffic monitoring and management developed by PTV’s subsidiary SISTeMa in Italy:
It produces off-line estimations, real-time flow and travel time prediction (30 minutes forecast).
It produces a traffic estimation during each day-type (based on an offline DTA model – VISUM) which can be later calibrated through real-time measures.
The product was especially conceived for metropolitan areas because the congestion is stronger, but it can also be applied in non-urban areas.
Computational times are relatively short. For the area of London being currently tested, a single program run (including the calculation of the current state, plus five forecasts (one for the do-nothing scenario, and four looking at other potential scenarios)) takes less than 2 minutes.
The outputs of the model could be used to serve information to the travelers through in-vehicle navigation systems, websites, or message signs located along the network. They can also be used to manage the traffic system by modifying the signal controls.
The software offers the possibility to manually insert events in the network. It also responds to events that are automatically inserted. It is possible to modify characteristics of the network (e.g. adding bottlenecks, changing cycle times of traffic lights, closing streets).
The user can select among different Key Performance Indicators to evaluate the multiple scenarios (e.g. travel time (h), average speed (km/h), total queue (number of vehicles), total travel distance (km)).</td></tr>
<tr><td>Scenario generation:</td><td>Scenarios can be designed based on specific events, demand patterns, or signal plans. Currently they are manually selected.
For example, tests are being carried out where the Traffic Control Center designs different scenarios by proposing different combinations of signal plans. For that they employ pre-defined signal plans using the adaptive traffic control system SCOOT. SCOOT optimizes the performance of the network, in almost real-time, by changing traffic signal times according to the traffic conditions.</td></tr>
<tr><td>Data collection:</td><td>Loop detectors.
Pre-defined signal plans (only historical information).</td></tr>
<tr><td>Interventions:</td><td>There is nothing on-line yet, as the different software is now being tested.</td></tr>
</table>

Open Issues:	▪ No information has been found.
Other:	▪ Current efforts are part of London's long-term strategy on Intelligent Traffic Systems, which includes improvement of data collection capabilities, prediction algorithms, and decision support modeling for better management of the network.
References:	▪ Gardener, K. (2011) London's Intelligent Traffic System, presentation for IMPACTS Europe Conference, Barcelona. ▪ Krishnan, R., V. Hodge, J. Austin, J. Polak, T. Jackson, M. Smith and T.C. Lee (2010) Intelligent decision support for traffic management, Proceedings of the 17th ITS World Congress, Busan, Korea. ▪ Meschini L., Gentile G. (2010) Real-time traffic monitoring and forecast through OPTIMA – Optimal Path Travel Information for Mobility Actions, in Proceedings of Models and Technologies for Intelligent Transportation Systems, International Conference Rome 2009, ed.s G. Fusco, Aracne, 113-121. ▪ Möhl, P. (2011) Use cases of Intelligent Traffic Management, Presentation for PTV Traffic Mobility Logistics. ▪ Möhl, P. (2011) Yellowhead Trail ITS Simulation Laboratory and Edmonton Showcase, Presentation for PTV Traffic Mobility Logistics.

6.6 Case: Naples

City/Country:	▪ ***Naples / Italy***
Organization:	▪ Work supported by: - The European Commission Information Society Technologies (IST) Program through the project RHYTHM under Grant IST-2000-29427. - The Italian Ministry of University and Research through the project PON-SAM under Grant 12897. - The Engineering New Staff Research Fund of Monash University (2009 and 2010).
Type of network, size:	▪ Motorway - A3 freeway between Naples and Salerno in southern Italy (100 km stretch)
Time line:	▪ Trial period: May 25, 2006 (11 hours). ▪ It is currently operational.
Objectives:	▪ To provide information: Estimating and predicting future traffic states (including travel times). ▪ To detect incidents.
Software:	▪ RENAISSANCE is a generic real-time freeway network traffic surveillance tool based on macroscopic traffic flow modeling and extended Kalman filtering (EKF). ▪ The model includes multiple fundamental diagrams to address traffic flow inhomogeneity. ▪ The driver behavior at bifurcations is modeled in terms of turning rates. ▪ The model describes traffic flow dynamics in a freeway network of any topology, size, and link characteristics; and simulates all kinds of traffic conditions (free flow, dense, and congested), as well as capacity-reducing events (e.g. incidents). ▪ The model step time is set equal to 5 seconds. ▪ Traffic state prediction is performed within a 10-minutes time horizon. ▪ RENEAISSANCE is integrated with a dedicated graphical user interface (GUI). This GUI can be used for a complete presentation of real-time traffic state estimation results. In real-time operation, the GUI view is updated at the same time as the measurements are updated. ▪ Each link (headed by an arrow) is displayed along with its segments, each with a length of approximately 500 m. The width of each segment is proportional to the estimated segment flow, whereas the colors of each segment correspond to the following estimated speed levels: - Green for free-flow conditions, with the segment's space mean speed exceeding 90 km/h. - Yellow for dense flow conditions, with the segment's space mean speed between 40 km/h and 90 km/h. - Red for congested conditions, with the segment's space mean speed below 40 km/h. ▪ The model represents traffic flow dynamics along freeways stretches using aggregate traffic flow variables (e.g. flows, space mean speeds, and densities). ▪ It uses the conservation equation, continuity equation, and dynamic-speed equation which includes a steady speed-density relationship from which the fundamental diagram is derived.
Scenario generation:	▪ Project focuses on providing information and not on developing control strategies. Hence, only a single prediction (based on current state) is made.

Data collection:	- Video detectors that offer flow and speed measurements. They are installed in both directions with an average spacing of 4 km for the 20 km section at the Naples side, and an average spacing of 6.9 km for the other 27.5 km section - Toll stations that record the number of passing vehicles. - The measurements update interval is irregular but about 30 seconds on average.
Interventions:	▪ During the trials, no information was served to the users of the road. No information was found regarding the current procedure.
Open Issues:	▪ The number of traffic state variables to be estimated is more than 500, whereas the detectors and toll stations deliver measurements for 59 flow variables and 46 speed variables only. Hence, the majority of the state variables of interest have to be estimated from very limited measurement data.
Other:	▪ Floating-car data that reflect real travel times were not available during the test period; therefore, RENAISSANCE's travel time prediction function was not evaluated. ▪ Chart below shows the architecture of REINASSANCE

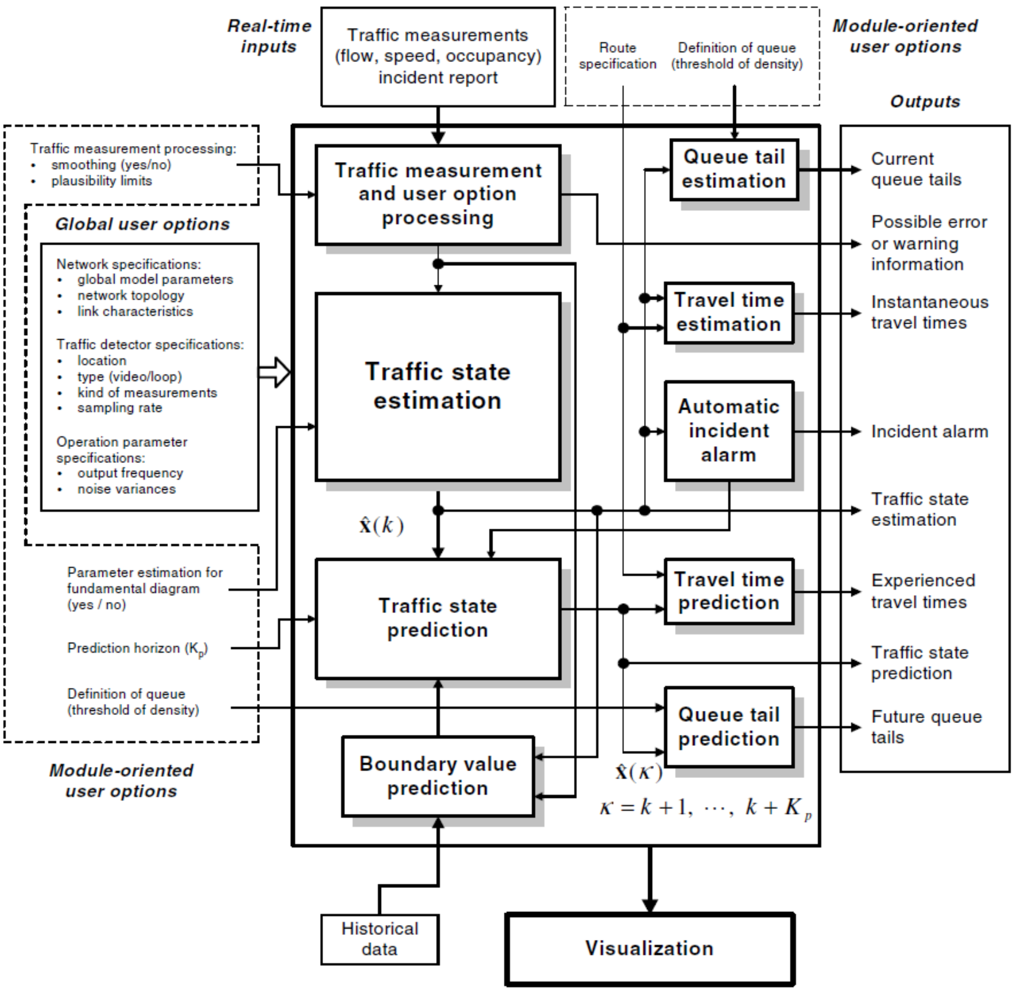


Figure 9. Architecture of the Naples model. Source: Wang (2006).

References:	▪ Wang, Y., M. Papageorgiu, A. Messmer (2006) REINAISSANCE: A Real-Time Freeway Network Traffic Surveillance Tool, Proceedings of the 2006 IEEE Intelligent Transportation Systems Conference, Toronto, Canada. ▪ Wang, Y., P. Coppola, A. Tzimitsi, A. Messmer, M. Papageorgiu and A. Nuzzlo (2009) An adaptive freeway traffic estimator, Automativa 45, 10-24. ▪ Wang, Y., P. Coppola, A. Tzimitsi, A. Messmer, M. Papageorgiu and A. Nuzzlo (2011) Real-Time Freeway Network Traffic Surveillance: Large-Scale Field-Testing Resoults in Southern Italy, IEEE Transactions on Intelligent Transportation Systems 12 (2), 548-562.

6.7 Case: North Rhine-Westphalia

City/Country:	▪ *North Rhine-Westphalia*
Organization:	▪ The project was initiated by the Ministry of Transport, Energy and Spatial Planning of Nordrhein-Westfalen. The development and tests were done in the framework of a research project at the University Duisburg-Essen.
Type of network, size:	▪ Motorway - North Rhine-Westfalia motorway network, with an area of 34.083 km2, approximately 18.075.000 inhabitants, and overall length of 2.173 km, 876 on- and off-ramps and 73 highways intersections. Average traffic load of 30.000 veh/day, with 15% trucks.
Time line:	▪ Trial period: 2000 - 2004. ▪ It is currently operational.
Objectives:	▪ To provide information: Informing the road users fast and efficiently about the current and future traffic states.
Software:	▪ Designed for a microscopic simulator. - It divides the network into links. - The main links connect the junctions and highway intersections. - Each junction and intersection consists of multiple links, such as on-and off-ramps or turning lanes. - Attributes (e.g. length, number of lanes, speed limit) are assigned to each link. - A link with its attributes is called track. - Each track is divided into the cells that are needed for the cellular automaton traffic model. - The junction of two tracks is called exit. It comprises all the important information that is needed by the simulation model. - The position of the loop detectors (called checkpoint) is also included in the digital map. ▪ OLSIM (OnLine Traffic SIMulation): Based on a cellular automaton model for traffic flow that reproduces the characteristics of real traffic. - For all loop detectors three dimensional classification vectors are used, according to weekdays, holidays, and special days. - Forecast data include traffic flow of all vehicles, flow of trucks, velocity of passenger cars, velocity of trucks, and occupancy. - Jams are identified when the density is larger than 50% (criteria motived by empirical studies). - Olsim Track Data Format (OTDF) is a geographic information system that has been
Scenario generation:	▪ Project focuses on providing information and not on developing control strategies. Hence, only a single prediction (based on current state) is made.
Data collection:	▪ 4.480 loop detectors that collect traffic flow, velocity and occupancy data. They can differentiate trucks and passenger cars. ▪ Secondary data: - Control states data from 1.800 variable message signs located across the network are provided every minute.

	- Location and duration of road works. Information of short term construction areas daily collected. Information of permanent construction areas weekly collected. - Radio Data System / Traffic Message Chanel (RDS/TMC-messages) provided by the traffic warning service including current traffic information, traffic jams, accidents, road closures and re-routings.
Interventions:	▪ A public website (www.autobahn.nrw.de) is designed to offer traffic information to the general public. It offers a map of the motorways of the region of North Rhine-Westphalia. Its different parts are colored according to their specific traffic state: - Light green for free flow - Dark green for dense flow - Yellow for stop and go traffic - Red for a traffic jam The user of the website can select whether he wants to see: - The current traffic state - 30 minute forecast - 60 minute forecast
Open Issues:	▪ Future research aims to incorporate the feedback of the forecasts on travel behavior (i.e. decisions made by drivers based on the provided information).
Other:	▪ Chart below shows the architecture of OLSIM. Note that both primary and secondary data are used in the forecasts. Source: Chrobok (2005).

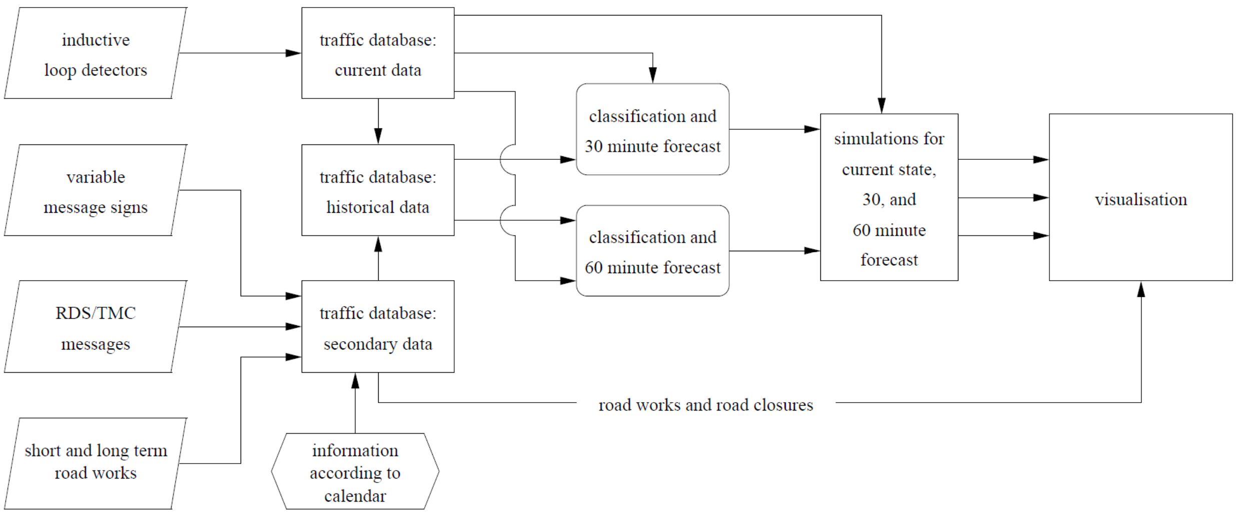


Figure 10 Architecture of the North Rhine-Westphalia model. Source: Chrobok (2005).

References:	▪ Chrobok, R. (2005) Theory and Application of Advanced Traffic Forecast Methods, PhD Dissertation, The University of Duisburg-Essen. ▪ Chrobok, R., S. Hafstein, A. Pottmeier and M. Schreckenberg (2004) OLSIM: Future Traffic Information, Proceedings of the IASTED International Conference, Applied simulation and modelling, 341-346. ▪ Schadschneidera, A. W. Knospeb, L. Santenc and M. Schreckenbergb (2005) Optimization of highway networks and traffic forecasting, Physica A 346, 165-173

6.8 Case: Rome

City/Country:	▪ ***Rome / Italy***
Organization:	▪ OCTOTelematics in collaboration with Autostrade per l'Italia Spa (leading Italian concessionaire for toll motorway) and ANAS (Road and Motorways Authority of Italy).
Type of network, size:	Motorway – Rome Ring Road (GRA-Grande Raccodro Anulare, 68,2 Km). ▪ Toll-free motorway that encircles Rome with 6 lanes (3 per direction) in 97% of the road (on April 2008 during the trials). ▪ Major traffic city traffic artery with 33 entry/exit junctions. ▪ Heavy traffic most of the day (i.e. frequent delay and traffic jams due to accidents or queue spillbacks from the ramps or the adjacent arterial streets).
Time line:	▪ Trial: January 2008 – April 2008 ▪ Currently, only the real-time traffic state information is operational. No prediction service is available.
Objectives:	▪ To provide information: Predicting future traffic flows (15 and 30 minutes forecast) based on current traffic flows.
Software:	▪ For the short-term predictions of link travel speeds (15 and 30 minutes forecasts) two algorithms are tested: Pattern Matching and Artificial Neural Networks. They are chosen because they can take into account spatial and temporal average speed information simultaneously. ▪ A Pattern Matching is useful when base data is already classified into categories. The method looks at speed data as a categorical time series, that is when speed data are offered over a regular time sequence as quantized into interval data. In the test 4 levels were defined: - Free for speed > 90 km/h, - Conditioned for speed 50- 90 km/h, - Slowed for speed 30-50 km/h, - Congested for speed < 30 km/h. ▪ Artificial Neural Networks are a multilayer feedforward neural network combined with a backpropagation algorithm which can predict the link travel speeds when base data is expressed in km/h, so no categories are needed.
Scenario generation:	▪ Project focuses on providing information and not on developing control strategies. Hence, only a single prediction (based on current state) is made.
Data collection:	▪ Floating Car Data. Cars equipped with GPS receiver and GSM/GPRS transmitter which can collect: - Average travel times, speeds and direction along road links. - Incidents or critical situations (accident detection and reconstruction). - Origin-Destination traffic flow patterns. - Statistics on driver behavior. The data is periodically transmitted (on request or automatically). OCTOTelematics has more than 600.000 on-board units installed in Italian private cars (data from 2008), and expecting an increase of 30.000 units per month. This represented 1,7% of the total cars in Italy at the time of the trials, 2008. ▪ 15.000 floating cars pass though the GRA every day, and during the pick hours 2000 vehicles per hour. ▪ Average distance traveled by a floating car on the GRA is 10 Km.
Interventions:	▪ Offer information to the public users in the web site

	http://traffico.octotelematics.it/index.html, where the user can find the average speed estimated in the different links of the network plotted in different colors according with the average speed: - Green for speed > 90 Km/h - Blue for speed 70-90 Km/h - Yellow for speed 50-70 Km/h - Orange for speed 30-50 Km/h - Red for speed 10-30 Km/h - Black for speed < 10 Km/h ▪ Estimated speeds are delivered, for real-traffic information, to: - Infomobility service providers - Motorway/roadway operators - Radio stations ▪ No further information (i.e. forecasts) was provided during the trials.
References:	▪ De Fabritiis, C., R. Ragona and G. Valenti (2008) Traffic estimation and prediction based on real time floating car data, Proceedings of the 11th International IEEE, Conference on Intelligent Transportation Systems, 197-203.

6.9 Brief Overview Of Other Trials

The following cities might also have (had) some applications, although there is no much information available:

Torino:

Background:	▪ 5T manages the Traffic Operation Centre in the metropolitan area of Torino, integrated with the Public Transport real-team Monitoring System (AVM). 5T is one of the main actors in the Regional Infomobility Plan. It is managing the extension of the traffic monitoring and information system to the whole regional territory. 5T is also coordinating the BIP project (Biglietto Integrato Piemonte) that will introduce a single contactless ticket for the purchase of any mobility service in Piemonte.
Objectives:	▪ Design, develop, implement and manage ITS solutions and info-mobility services, aimed to achieve the following goals: - improve the traffic fluidity in the urban area and reduce congestions; - improve real time information services for the mobility; - improve quality and performance of monitoring services for the public transport fleets; - reduce air pollution caused by traffic.
Systems:	▪ Traffic Operation Centre and variable message signs panels (VMS) that provide information about traffic conditions and parking availability in the metropolitan area. ▪ Urban traffic Control (UTC) that improves traffic conditions and provides "green light" priority to public transport in the city of Torino. ▪ Limited traffic zone (ZTL) that controls vehicles access in the Torino city center. ▪ Video-surveillance on GTT busses and at bus stops in Torino. ▪ Internet trip planner that provides citizens real arrival times at bus stops, best path calculation, real time availability in the parking areas. ▪ Public transport information services (bus stop displays, on-board displays, sms, voice).
Website:	▪ www.5t.torino.it/5t/en/home.jsp
Software used:	▪ Utopia UTC Strategies
References:	▪ www.ertico.com/assets/download/peace/session1_mizar.pdf

Bavaria:

Background:	▪ The Free State of Bavaria cooperates with VIB (Bavarian Traffic Information Agency) that has established and operates a Bavarian-wide platform for travel and traffic information. The Free State of Bavaria provides its services "Traffic Condition", "Travel Information" and "Bavaria's Cycle Network" free of charge to the public.
Website:	▪ www.bayerninfo.de
Software used:	▪ VISUM.

Antwerp

- Offline trials were performed here with RENAISSANCE and VISUM.

7 Conclusions and Recommendations

7.1 Introduction

In this last chapter, we put forward the main findings, conclusions and recommendations of the state-of-the-art and the state-of-the-practice reviews. The recommendations can be categorized into recommendations for practice and for future research work. While the former focuses on issues that can be implemented directly by practice, the latter stresses which applied or scientific research needs to be performed with respect to the subject of the STEP project. In this section, we provide a short overview of the main findings from the state-of-the-art and the state-of-the-practice.

7.1.1 State-of-the-art

The state-of-the-art provided an overview of the short-term forecasting methods, decision support systems, and control approaches that have developed over the years. Regarding short-term forecasting, the following categories were distinguished:

- Naïve methods (using the current state or historic averages)
- Parametric model approaches using traffic flow models or simulation
- Parametric model approaches using statistical techniques (time-series models, regression, etc.)
- Non-parametric approaches (ANN's, clustering techniques, etc.)

Many of the short-term forecasting applications proposed in scientific literature focus on freeways (on the contrary to the practical studies, of which many also consider urban networks). Few of the applications discuss network wide and in mixed urban and freeway environments, while this seems to be a key aspect given the future applications in traffic management.

Taking a look at the state-of-the-art in DSS (Decision Support Systems), we see again that many approaches have been put forward in the last few decades, covering a variety of functions. In general, these functions can be divided into:

- Problem identification (detection and diagnoses)
- Generation of possible solutions (also referred to as scenario generation in the ensuing)
- Prediction, either pertaining to the prevailing condition or to a 'what-if' situation (scenarios)
- Advising, that is, providing the operators with an advice (possibly based on the preceding functions).

Many techniques have been proposed (knowledge-based, case-based, rule-based, model-based), none of which seem to 'dominate the scene'. A key problem here is the 'curse of dimensionality', that in particular hampers application of case-based and rule-based systems. To resolve this issue, division of the network into sub networks has been applied in several approaches.

Finally, the state-of-the-art has reviewed the different approaches proposed for controlling traffic in regional networks (urban and motorway). Note that this strongly relates to some of the functions of DSS's described above.

Also here, a distinction is made between case-based, rule-based, optimal-control and model-predictive control (MPC). Furthermore, centralized, hierarchal and distributed systems where considered. The different approaches have been compared using a number of criteria, such as the level of information required, the quality of the control, the complexity of the approach, the ability to consider multiple measures jointly, the scalability of the approach, and finally the effort to apply the method in practice. The table below provides and overview of the main findings (see §6.6 for more information).

Table 5 Feature comparison for different control methods

Method	Information	Quality	Complexity	Integration	Scalability	Effort
MPC (centralized)	Global	High+	High	Yes	No	High
MPC (hierarchal)	Compromise	High	High	Yes	Yes	High
MPC (distributed)	Local	High	High	Yes	Yes	High
Optimal control	Global	Medium	High	Yes	No	High
Rule-based	Compromise	Medium+	Low	Possible	Yes	Medium
Case-based	Compromise	Medium+	Medium	Yes	Yes	Medium
Anticipatory control	Global	High+	High	Yes	No	High
MFD-based	Global	Medium-	Low	Yes	Yes	Low

The table clearly shows the trade-off between the different characteristics of the approaches, in particular in terms of effort/complexity and quality. None of the approaches is dominant in every performance aspect. Some, however, seem to be less appropriate candidates for traffic control applications (optimal control, anticipatory control and centralized MPC) because of their high complexity and difficult scalability.

7.1.2 State-of-the-practise

The state-of-the-practice in short-term forecasting has reviewed a number of applications throughout Europe, which are generally focusing on providing information to either the operators or to the road-users. The table below shows an overview of the reviewed applications and their key characteristics.

Table 6 Overview of reviewed application and their key characteristics.

Case	Objective	Network type	Method	Input data	Prediction horizon	Scenarios	Validated
Berlin	Information provision	Urban	Model-based (VISUM on-line)	Detectors providing flows and speeds, PT data, webcams, FCD from busses and taxis	30 min	No	Limited
Dusseldorf	Information and control	Urban	Model-based (PTV Traffic Platform)	Loops, signal information, incident information	60 min	Yes, user-input	Unknown
Helsinki	Information provision	Motorway	Data-driven (ANN's)	Camera's	15 min	No	Partially
London	Information and control	Urban	Model-based (OPTIMA)	Loops and pre-defined signal plans	30 min	Yes (demand patterns, signal plans, events)	No (system not yet operational)
Naples	Information and incident detection	Motorway	Model-based (RENAIS-SANCE)	Video (flow, speed), toll-stations	10 min	No	Unknown
North Rhine-Westphalia	Information provision	Motorway	Model-based (microscopic simulation using CA; OLSIM)	Loop detectors, control settings	30-60 min	No	Unknown
Rome	Information provision	Motorway	Data-driven (pattern matching, ANN's)	FCD (GPS)	15-30 min	No	Unknown

From the table it becomes clear that the majority of the applications focus on providing information to the road-users. A wide range of data is used, but the loop detector seems still the dominant data source. The applications generally focus on either the urban network or motorway corridors or networks; none of the applications has considered integrated regional networks (although this may be possible given the applied methodologies). Finally, we can observe that (structured) validation efforts are very few and often limited to ad hoc observations concerning anomalies in the state estimations and predictions.

7.2 Conclusions

Given the findings described in the previous section, this section presents the main conclusions for this review. From the state-of-the-art review, the following conclusions are emphasized:

In order for the methods proposed in literature to be used in practice, they should be able to predict traffic on a larger, regional scale, rather than on (isolated) freeway stretches only. In particular for future applications, short-term forecast on a regional scale will become more and more important.

An important advantage of traffic models over statistical (data-driven) non-parametric approaches is that they can be used for network-wide traffic predictions. Moreover, because traffic flow models capture the fundamental properties of traffic flow, they improve consistency between measurements, guaranteeing physical principles like conservation of vehicles on links and over nodes. This also renders them capable of modeling unforeseen situations such as incidents, which pose a problem for non-parametric models.

Overall, the validity of the predictions has not been extensively considered (not in the state-of-the-art; not in the state-of-the-practice), neither for predicting prevailing conditions (i.e. the ‘do nothing scenario’), nor for testing the quality of the different scenario predictions (e.g. studying the impact of incidents, control interventions, etc.).

Is it not easy to decide the most suitable control approach, such it strongly depends on the preferences regarding the development and implementation effort compared to the expected prediction and control quality. Nevertheless, Model Predictive Control (in particular hierarchal or distributed) or rule-based / case-based systems seem good candidates for practical applications, where MPC offers better quality at the expense of considerable effort in terms of development and implementation.

Literature provides limited information about model identification and calibration issues. More insight into the relation between prediction quality and control quality is required. This holds for the model parameters (e.g. capacity, critical density, etc.), for the OD’s (demand forecast, which are critical in resulting in accurate model predictions), as well as the initial state (in relation to state-estimation techniques). Chapter 7 has discussed some of these issues in more detail. This leads to the following sub-conclusions:

- parameter identification for short-term forecasting needs further attention, which pertains to the identification techniques, identifying good performance indicators, etc.;
- there is insufficient insight into the relation between data quality (accuracy, reliability, timeliness, completeness) and estimation / prediction quality; and
- there is insufficient insight into the relation between prediction quality and control effectiveness / performance.

The applicability of MPC for realistically sized networks may become computationally intractable, unless simplified models are used. Again, the trade-off between model complexity (and thus speed of computation) and prediction quality is a subject in which more insight is needed.

From the state-of-the-practice, the following conclusions can be made:

- Most existing applications focus on providing information, and not on the generation and assessment of control strategies. Most cases do not include scenario generation algorithms. As a matter of fact, in the cases where multiple scenarios were tested, such scenarios were manually input into the system.
- From personal interviews with representatives of software developing companies involved in short prediction modeling, most of the issues nowadays seem to be related to data collection. This includes lack of devices (or lack of properly working devices), and/or lack of integration protocol across different data collection systems (e.g.,p reports and Transportation Authorities measurements). Nevertheless, those issues were not mentioned in most of the papers reviewed.
- Even though most modeling software often have the capability to deal with Floating Car Data (FCD), rarely any system does (largely due to the lack of data availability).
- Since most of the applications so far have focus on providing information to users, they typically have relatively easy/efficient user interfaces. This includes color-coding of the links according to traffic flow levels, etc.
- Current applications cover motorway links, motorway networks, and urban networks. No apparent bias towards a specific type of network was found.
- Although many of the existing software can detect incidents (i.e. congestion issues), often they cannot distinguish between recurrent and non-recurrent congestion (i.e. type of incident).

It should be noted that it was not easy to find information about the practical applications. Given this lack of public information regarding many of these applications, the focus of Work Package 2 will be useful in terms of the information obtained through discussions proposed to be held with individual Traffic Management Centres. We believe there is value in requesting an in-depth feedback regarding the implementation process, major milestones, open issues, etc.

7.3 Recommendations

This section summarises the main recommendations for practice based on the findings and conclusions in this Work Package.

7.3.1 Need for short-term forecasting

One key recommendation, which has not been explicitly considered in the review, is the *need* for short-term forecasting. From the state-of-the-art and the state-of-the-practice it becomes clear that short-term forecasting is technically feasible. The state-estimation and prediction techniques are there, and, although further work on calibration and validation is required, can be applied in practice. The benefits of using predictions are evident: better information for the road authority and for the road-user (predicted vs realized travel times), the ability to anticipate on future conditions rather than to (over-) react on the current situation, the ability to predict the impact of control interventions, and of events, etc.

7.3.2 Model-based Versus Data-driven Approaches

One of the conclusions reflects the choice for a particular method for prediction for information provision, for decision support and for control intervention. Based on the results of the state-of-the-art and the state-of-the practice, model-based approaches show many advantages compared to data-driver approaches. In particular the ability to deal with non-recurrent conditions, changing in the demand profile, incidents, as well as the ability to predict the impact of control interventions, provides large benefits. It was found that data-driver techniques (such as ANN's, Bayesian networks, etc.) have difficulty to respond adequately to aforementioned changes.

7.3.3 Scenario-based Versus Optimization Approaches

Choosing between scenario-based (or case-based) approaches and optimization approaches (MPC) is less obvious. Both approaches have their specific drawbacks and benefits. On the one hand, scenario-based approaches are more transparent (the users sees which scenario's are assessed, can change the scenario's, etc.) compared to optimization approaches, which are perceived as black boxes by many operators. Furthermore, they require (far) less effort to implement in practice. On the other hand, MPC yields more efficient controllers (at least in theory!) since they can optimize the utilization of the network given predicted network conditions.

One aspect of importance here is the generation of the scenarios, which still in an area of research (although some operational systems are available, e.g. in the Regional Traffic Management Centre in North-Holland, Amsterdam area; (Wang et al, 2010)).

7.3.4 Regional Approaches

All of the approaches reviewed in this report either consider the urban network or the motorway network. To use the available network as efficiently as possible, an integrated approach is recommended in which both types of networks are considered jointly. At least some of the reviewed systems can deal with these networks, although in many cases, effort has to be invested in technologically joining the networks (e.g. integration of data collection and actuator control; concentration of activities in a single traffic management centre, etc.). Nevertheless, we argue that the benefits of such an integrated regional approach will be large.

7.3.5 Monitoring Effectiveness

Cost-effectiveness of traffic management has been debated vigorously over the past and this will probably continue over the years to come. It is therefore pivotal to not only invest in the implementation of traffic management systems (both in terms of the technology and methodology), and in keeping these systems functioning, it is also very important to monitor the impacts on the network performance of these systems. First of all, this will provide better insights into the effectiveness of traffic management in general, and the impact of using short-term forecast in day-to-day operational traffic management specifically. Second of all, it will provide data based on which the systems can be improved. It is quite surprising that in none of the considered applications, the *impact* of the system was extensively described. These insights are essential to convince policy makers to invest in such systems in the future.

7.4 Research Recommendations

Based on the review performed in this Work Package, several recommendations for research can be made which are relevant for the work performed within the STEP project.

7.4.1 Scenario generation and assessment

Scenario generation and assessment has been considered in literature at several instances. However, in practical applications, this aspect has not received much attention. It is therefore recommended to investigate further practical scenario generation schemes, based on the different examples that have been put forward in literature.

An important issue here is to keep the number of scenarios within reasonable limits. The state-of-the-art briefly mentions approaches to do this, generally based on the use of sub networks. At the time of writing, one application is operational in which scenarios are constructed using sub networks (operational in the Verkeerscentrale North-Holland, Amsterdam; (Wang et al, 2011)). The Scenario Coordination Module generates (control-) scenarios per sub network using so-called building blocks. These scenarios are checked by the operators and could subsequently be assessed using short-term forecasting approaches. Other approaches are possible as well, and need to be investigated further in the future.

7.4.2 Model calibration and validation

In the state-of-the-art report, the issue of calibration of the forecasting model parameters has been briefly discussed. Based on the results, it becomes clear that this is an issue that deserves further deliberation (see also the open issue in the RENAISSANCE application in chapter 2, where the lack of data complicates the ability to estimate the large number of parameters in the model). Some important aspects that need further investigation are:

- Parameter (capacities, jam densities) and model input (OD predictions) identification methodology,
- Data requirements (quality, quantity, semantics, etc.), and
- Model performance assessment criteria (that is: develop measures that reflect the key flow characteristics that need to be capture by the model)

During this review, we observed that the validation of the forecasting models has received little attention so far. We therefore recommend developing a framework for model validation (including the development of relevant performance assessment criteria) and benchmarking.

7.4.3 Relation between data quality and estimation / prediction performance

Evidently, the quality of the data will determine the quality of the estimations and predictions, and in turn the effectiveness of the control actions based on these estimations and predictions. However, the relationship between the quality of the data on the one hand, and the quality of the estimations and predictions is by no means clear.

We therefore recommend to investigate this further, as well as to investigate to which extent the data quality can be increased by advanced state-estimation and data fusion techniques. It should be noted that in literature, several results regarding this subject are available in particular focusing on state estimation (rather than prediction).

A key aspect of this subject, are the data quality requirements that stem from this analysis. In other words, which data collection system, possibly including data collection techniques that provide data with different data semantics, needs to be installed to provide state estimates and predictions that provide results that are of sufficient accuracy given the intended application. Note that such as system would be described at the functional level, rather than at the technical level (i.e. describe the characteristics of the data it needs to collect in terms of semantics, accuracy, reliability, availability).

7.4.4 Quality of Estimation / Prediction Performance and Control Performance

As mentioned in the preceding subsection, we lack insight into the relation between the quality of the state estimates and the predictions, and the eventual control decisions that are made on the bases of these estimations and predictions. Acquiring such insights will effectively ‘close the loop’ from data quality to control effectiveness, allowing monetizing the benefits of installing better data collection systems using the increases in effectiveness (in other words: what is the added value of an additional loop detector).

7.4.5 Computational Complexity and Efficiency Trade-off

Models come in various shapes and sizes. Generally speaking, the more complex the model is, the more accurate the predictions it provides. This increase in accuracy comes at a price: higher computational demand and loss of tractability.

What is still tractable depends on the application at hand. For one-scenario predictions, complex models can be used. In fact, in the state-of-the-practice examples of microscopic simulation models have been put forward. When more scenarios are to be assessed, or applications to larger regional networks are foreseen, such models may yield unacceptable computation times and less complex (e.g. macroscopic) models may be more appropriate.

For model-based optimisation problems, additional issues are to be considered. First of all, MPC schemes often used iterative solution schemes to look for the ‘predicted optimal solution’. That is, the model will be run multiple times, depending on the size of the control vector and the complexity of the network. Furthermore, application of non-linear models or non-quadratic optimization functions strongly complicates finding the optimal solution. As a result, one may consider simplifying the prediction model (e.g. approximation by means of a linear model) in order to guarantee quick (and reliable) convergence of the optimization problem (making solving the problem using standard solvers possible). The extent in which this will affect the quality of the control strategy needs to be investigated.

As well as computational demand, the identification issue cannot be disregarded: complex models are generally less parsimonious, and are hence harder to identify based on available data. Furthermore, the likelihood of over-fitting becomes larger, as the model becomes more complex.

In summary, it remains to be seen what appropriate levels of predictive accuracy are available for the different applications of short-term prediction models, especially when we take into consideration the high level of noise on the input of these models (e.g. demand profiles), and the inherent uncertainty in the process that we are trying to describe (e.g. capacity fluctuations).

7.4.6 Advanced Data Collection and Traffic Actuation Techniques

In the state-of-the-practice it was observed that the use of alternative data sources is regularly discussed. However, we have not seen many applications that make effective use of the characteristics of these new data sources. It is expected that their increased use will similarly lead to an increase in the quality of the estimations, and predictions (e.g. by data fusion, or by using the additional information which is contained in the data).

This is due to the different semantics of the data, which, when combined with more traditional data sources (i.e. data fusion) can lead to much better state estimates (Ou,2011). Secondly, new data sources may provide information, which has not been collected before (e.g. Bluetooth data providing information about route-choice and OD patterns). Using these data sources may substantially improve the quality of the estimations and the predictions, for instance by being able to observe and thus better model the impact of providing route guidance on the route choice given observed OD patterns. The possibilities of these new data sources need to be investigated further.

Appendix A. References

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