# INTELLIGENT ADAPTIVE TRAFFIC FORECASTING SYSTEM USING DATA ASSIMILATION FOR USE IN TRAVELER INFORMATION SYSTEMS

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**Abstract** In this paper we describe a novel application for data assimilation, a technique commonly used for atmospheric forecasting, in the area Traveler Information Systems. Our view is that the next generation of these systems will provide travel advise that employs not only the current traffic situation but also the future state of traffic. We show with actual traffic data that the impact of external influences (such as weather and large public events) are key to achieve accurate predictions. We propose an approach to model these influences in detail. Furthermore we describe how these detailed models can be combined with existing traffic models, using Data Assimilation. The results is an adaptive real-time system that can be used for intelligent Traveler Information Systems. We show our development and experimentation environment which offers solutions to the problems encountered in the development of the data assimilation system. Finally we discuss the progress and the challenges ahead.

**keywords: Traveler Information System, Intelligent Systems Engineering, Application, Data Assimilation**

## 1. Introduction to Adaptive Forecasting for Traveler Information Systems

This paper addresses the development of information systems in the Intelligent Transport Systems (ITS) domain, that are able to deal with the context of the user (adaptiveness) and are able to combine historical and real-time data (forecasting).

The employment of Traveler Information Systems has received a great deal of attention in the recent past and it is believed by both the research and commercial communities that traveler information is key to dealing with transport challenges in our congested societies. Current applications for instance are dynamic road displays which keep the traveler up to date with the current traffic situation. These displays give information about the length of traffic jams, about capacity reduction due to road works or lane closures or provide actual travel times over a given stretch of road. State of the art techniques employ the measured density of cellular phones on a stretch of road to derive the average driving time over that stretch[1]. Although the actual traffic situation can be accessed reasonably well, the use to the traveler is limited to information during the trip, or just before the trip. Services that predict the state of traffic are still in their infancy.

Another complexity is that the traveler can receive the same information by different means. Traditionally, the roadside displays are used for information distribution, but there is a strong growth in the availability of wireless devices which combine navigation, traffic condition monitoring and route guidance. This brings the question: what is the right information at the right time and how shall it be delivered to the user? It has become accepted that choice of delivery channel and content density are subject to the context of the user. Consequently, personalised information services require some form of machine intelligence to deal with the specific context of the user. Is the user traveling by car or public transport? What are the time constraints on a trip? What are the user interface capabilities and preferences? Research in this field is for instance carried out by the project PALS (Personal Assistant for onLine Services)Anywhere[11]. In this project, the development is studied of a personal assistant capable of supporting a user in different situational contexts by adapting the user interface and offering on-line help.

The PALS project illustrates an important aspect of the design and realization of information services, namely taking the individual user preferences as starting point. We have investigated this approach in the traveler domain[4] and found that, given an acceptable price level and trip duration, the key drivers for individual travelers to select between two ways of traveling are: predictability

[1] an example can be found at http://www.logicacmg.nl/mts

of the trip (forecast), the reliability that the forecast turns out to be correct, the comfort and safety enjoyed during the trip.

Forecasting thus takes a pivotal role in designing user oriented travel services. We believe that effective forecasting must on the one hand use detailed models to process the effects of congestion and weather on the traffic flow, but on the other hand also be able to employ empirical knowledge of the impact of for instance sports events or the start of the holiday season. There is therefore a great demand for a better understanding of combining historical and real-time data to make predictions of future travel conditions. These predictions are necessary when providing alternative routes to drivers in order to avoid congestion.

The traffic situation on the roads is a constantly changing process, thus a piece of road which is free from congestion at the time the route advise is given can be congested by the time a driver arrives there. This problem among others is dealt with by research commissioned by the FHWA[2]. In particular within DynaMIT[1], which is part of this research, the problem of prediction is addressed. It focuses on the problem created when a lot of travelers start taking alternative routes based on a predicted future state of traffic. The drivers reaction to the advise he is given will have to be taken into account when making predictions. Informed drivers will have to be modeled in the prediction process. Another factor that is recognised within DynaMIT as being important for the prediction of future traffic are external influences such as weather, accidents and large public events (sports events, pop festivals, parades etc..). This factor however is not the main focus of Dynamit and therefor not worked out in detail in their research. We propose that a detailed model of external influences can give a significant improvement to predictions of the future state of traffic. In the rest of this paper we will explain why we think this is the case and how we plan to implement such a detailed model.

In section 2 we will explain what influences are important, what the properties of different influences are and for some of them illustrate this with real world data on delays in traffic. In section 3 our approach to modelling these influences will be layed out. After that, in section 4, we will put forward a Data Assimilation system which combines external influences and existing traffic models to produce predictions of the future state of traffic. This is followed in section 5 by a description of the development environment. Finally we will briefly discuss some of the issues to be faced in this research and draw some conclusions.

[2] U.S. Department of Transportation Federal Highway Administration
http://www.fhwa.dot.gov

## 2. Importance of external influences

In this section we will look at the correlation between external influences (weather, special events and incidents) and the pattern of traffic. Furthermore we will analyse the implications of this correlation for the accurate (longterm) prediction of traffic and congestion. Over time traffic patterns have a large amount of variability. There are many causes for this variability, in order to explore these further we divide these causes into three distinct categories.

First there is nature, which is almost entirely accounted for by the weather. Different weather conditions such as rain, fog and snow cause different driver behaviour and therefor different traffic patterns.

Second there are the human causes, these consist of two sub-categories of global and local influence. The global events are calendar related phenomenon such as the difference between weekends and work-days but also less regular events such as holidays. These events have effect on the society or country in which this calendar is used unlike the second category which is bound to one geographical location. Large public events such as pop festivals, parades or demonstrations can cause an unusually high number of people to come to one place. Furthermore in case of demonstrations or parades streets can be closed causing a reduction in capacity. And more commonly road-works cause reduction of capacity somewhere in the road network on an almost daily basis.

The third category are incidents and accidents, these are a separate category because they have a bidirectional relationship with traffic patterns. They cause extra congestion and capacity reduction to happen, while these factors themselves influence the chance of accidents occurring.

For all of these factors at least some degree of prediction is possible. The likelihood of accidents is the most difficult to predict as it has many dependencies upon other uncertain information. The weather however can be accurately predicted up to 5-7 days ahead. Both the global calendar related events and the local events can be known for a time period reaching much further into the future. To illustrate the importance of external influences we present real world data on several calendar based events both with a global influence and with a very local influence. The data was obtained from our partner info.nl who are currently building a detailed database of all traffic-jams occurring in the Netherlands. Figure 1 shows the total length of traffic-jams in the Netherlands during the Good Friday holiday with two typical Fridays included for comparison. The graphs show that traffic on Good Friday is very different from a typical Friday, the morning rush hour is missing instead there is a prolonged peak later in the morning. In Figure 2 a similar situation is shown this time for Easter Monday. During daytime there are virtually no traffic-jams, however there is a prolonged peak in the evening. This in stark contrast to typical Mondays which show very distinct morning and evening rush hours. It is also

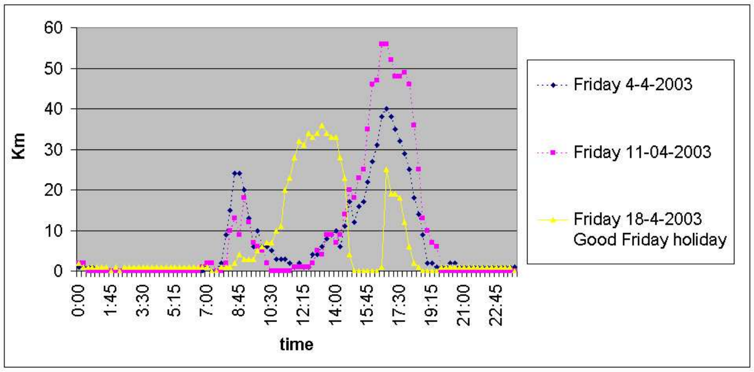


*Figure 1.* Total length of traffic-jams in the Netherlands on the good Friday holiday and two typical Fridays

worth comparing the normal Mondays and Fridays shown in Figures 1and 2 it is easy to see that different days of the week have different traffi c patterns. Fridays have a less pronounced morning rush-hour and an elongated evening rush-hour caused by people leaving home early for the start of the weekend. These examples showed a very strong global influence on traffi c. It should be noted that these fi gures present an abstraction of many local events the majority of which is an effect of the global influences. Local events can also occur without the existence of a global influence. Figure 3 shows the length of traffi c jams at the Amsterdam ring-road near the RAI exhibition centre. At Saturday 5-4-2003 a exhibition was being held which attracted 240.000 people over a nine day period. The graph shows a traffi c-jam starting just before 11:00 the opening time of the exhibition. It is very diffi cult to predict the traffi c-jams shown in these graphs without knowledge about their causes. Both Easter and Good Friday have different dates each year, although there is an exact pattern in their occurrence. Well attended exhibitions do not follow any exact pattern in time at all. Predicting these events only on the basis of historical traffi c data is unnecessarily diffi cult and will give less certain and accurate results than correlating traffi c data with its influences.

## 3. Modeling Approach

In this section we will outline our approach to modelling traffi c and its influences. We will describe the reuse of existing models, our approach to data aggregation and how to build redundancy into the model. For modelling traffi c itself we plan to use an existing model, many different traffi c simulators ex-

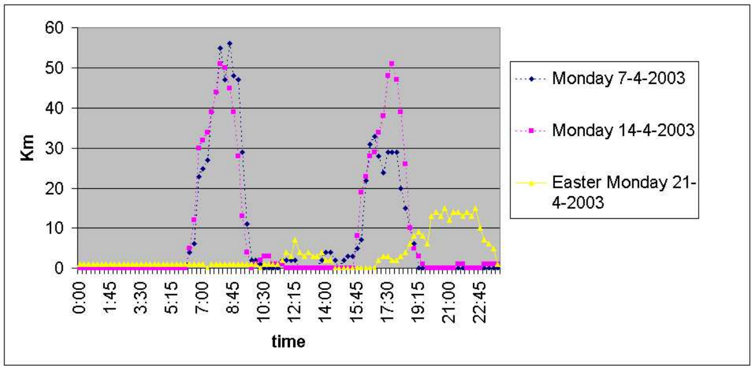


*Figure 2.* Total length of traffic-jams in the Netherlands on the Easter Monday holiday and two typical mondays

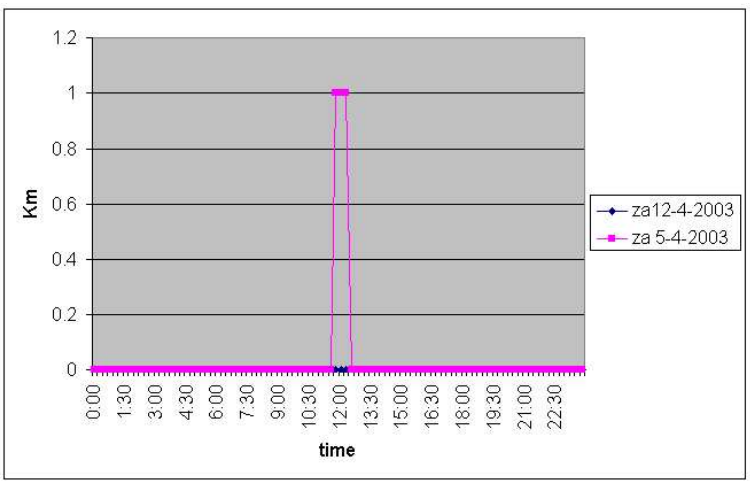


*Figure 3.* Length of traffic-jams near the ring-road exit for the RAI exhibition centre in Amsterdam during a well attended exhibition and on a typical saturday

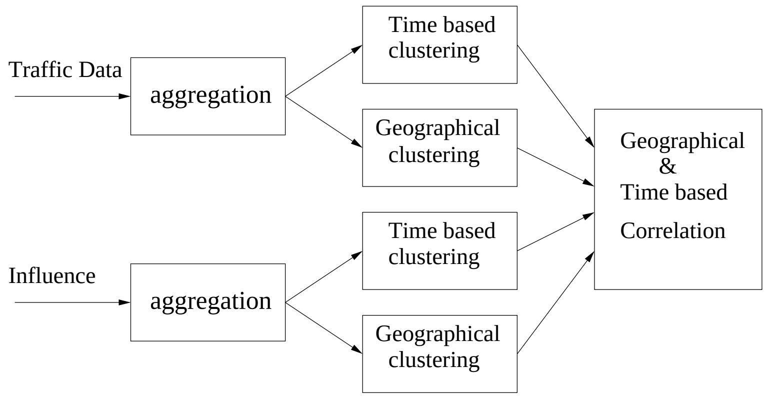


*Figure 4.* Proposed model for data aggregation and combination

ist [3] operating at different detail levels. Thus we will use an existing model with detailed modelling abilities with regard to traffic distributions as well as with an ability to take weather conditions into account. For weather prediction different models exist as well, however we do not need to model the weather ourselves we just need access to the data. Information about road works can be used by modelling it as a capacity reduction in the road network topology. Accidents are of a stochastic nature, predicting them and their impact on a detailed local level is not worthwhile. Once an accident is known to have happened it can again be modelled as capacity reduction in the road network topology. We do plan to explicitly model the impact of special events what follows is an explanation of some of the issues involved.

Our model has to correlate special events with traffic patterns, as illustrated by Figure 4 data has to be aggregated before it can be correlated. The raw data used as input is usually a series of observations from different locations at different times. By clustering this data one tries to identify distinct patterns, for instance within traffic and weather. Other data such as calendar data and information about events is discreet by itself so it does not need this step performed on it. When performing the clustering the next step in the process, correlation, has to be taken into account. As the examples of section 2 already showed, different influences act at different granularity both in space and time. Therefor correlation has to take place with data that is aggregated over the appropriate temporal an spatial intervals. This requires many aggregations to be performed on the incoming data, research by Johannes Gehrke et. al. [8] offers solutions in this area.

[3]The Smartest project coordinated by the University of Leeds has a very good survey of all the simulators and tools http://www.its.leeds.ac.uk/projects/smartest/

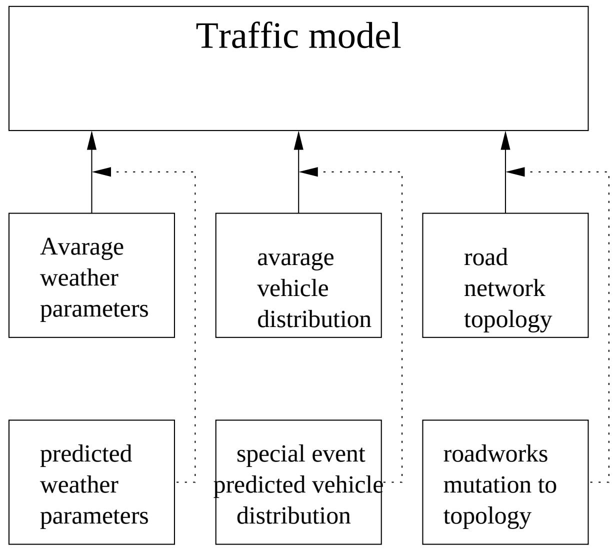


*Figure 5.* redundant modelling of external influences, solid arrows show data that can always be used, dotted is more detailed information that is used when available

An important issue that needs to be dealt with in a system that will be used for realtime data is redundancy. If a source of real-time data is unavailable or is not continues in nature the predictive model will need to have something to fall back on. This is illustrated in Figure 5. When current weather data is unavailable the model can fall back on average weather data of the season for the concerning area. The vehicle distribution will be based on averages for each day of the week, only when a data from special events suggests a significant change from the norm is this input changed. The traffic model needs to know the topology of the roads for which it makes predictions. Knowledge of roadworks should be reflected in the topology as a local reduction in capacity or even change in the topology when a road is closed completely.

## 4. Data Assimilation

Data Assimilation system described in this section takes a central role in our research. We focus on this subject not only because we believe it plays a central role in improving Traveler Information Systems but also because we believe that it has many more applications outside of its native domain which lies mainly in atmospheric, oceanographic and geographic prediction. This section describes how such a system will work and touches on some of the issues that will need to be resolved. The more general thesis we are trying to prove is:

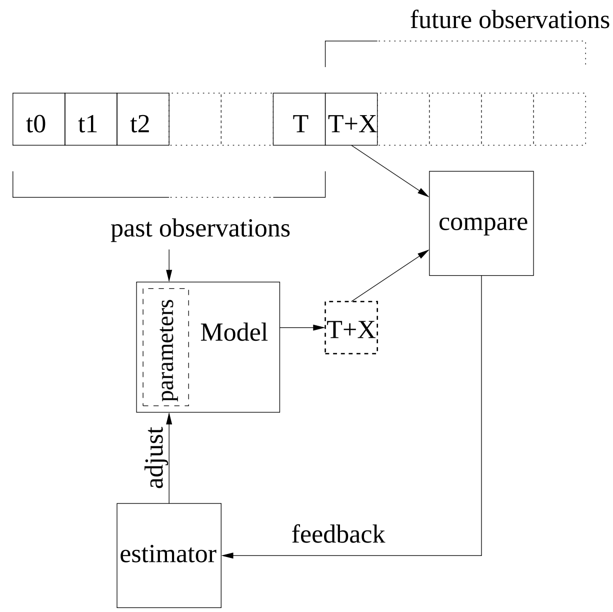


*Figure 6.* Data assimilation process

> **The successful application of Data Assimilation is not limited to the modeling and prediction of purely physical processes. It can also be used for prediction and modeling of behaviour based processes.**

In the case presented in this paper we want to predict a process which is based on the behaviour of car-drivers. To make our data assimilation system accessible to other applications we will develop it as a generic software component for the VL-E[6]. This Virtual Laboratory for E-science offers a front end to grid technology[5] in which researchers from different disciplines will be organizing and performing experiments. Developing our Data Assimilation system within VL-E not only provides accessability for other areas of research but also solves many issues regarding computing resources and data access.

Data assimilation is at the centre of our predictive system. First we will give a short description of what Data Assimilation does and what its principal components are. Data assimilation is used to minimize the error for predictive systems where there is uncertainty in both observations and the predictive model. The most obvious application of which is weather prediction. A data assimilation system in our view consists of:

- observation mechanism
- predictive model
- estimator

The predictive model takes the current state of the process that is modelled and produces a prediction on a part of the process for which there are no observations available. In case of both weather prediction and traffic forecasting this means predicting the state of the process at some time step in the future. The observation mechanism takes care of collecting measurements of the system that has to be predicted. These observations will have some degree of uncertainty in them. Ideally there are different types of observations which have different types of uncertainty and the nature of these different errors is known. The Data Assimilation system we are developing can take into account the following types of data sources.

- Historical data on behaviour
- Historical data on factors influencing the behaviour
- current data on behaviour
- current data on factors of influence
- predicted future data on factors of influence

The estimator minimizes the error by estimating what the initial conditions for a prediction produced by the model should have been. The classic and most well known example of an estimator is the Kalman Filter [9], but other methods such as Bayesian Maximum Entropy [10] exist as well. The estimator adjusts the parameters of the model relating to past and current observations. A process which we will explain in some more detail.

If current time is T the model makes a prediction about T+X where X equals the amount of time ahead the prediction has to be. When the current time has moved to T+X the prediction is compared with the actual observations at timestamp T+X. The Estimator adjusts the predictive model to the feedback received, after which the process is repeated with T equaling T+X.

To ensure that the predictions which are generated are consistent with reality, domain constraints and consistency filters have to be applied. In the traffic domain these can consist of information about the shape of the roadnetwork, and rules such as there can be only one trafficjam at a specific time and place.

The predictions resulting from the data assimilation system will be used to advise the user about the optimal route to take. The feedback mechanism as previously explained ensures that the predictive model constantly adapts to the current situation. To realise this Data Assimilation system within our Traveler Information System research we will take an experimental approach which we will outline in the next section.

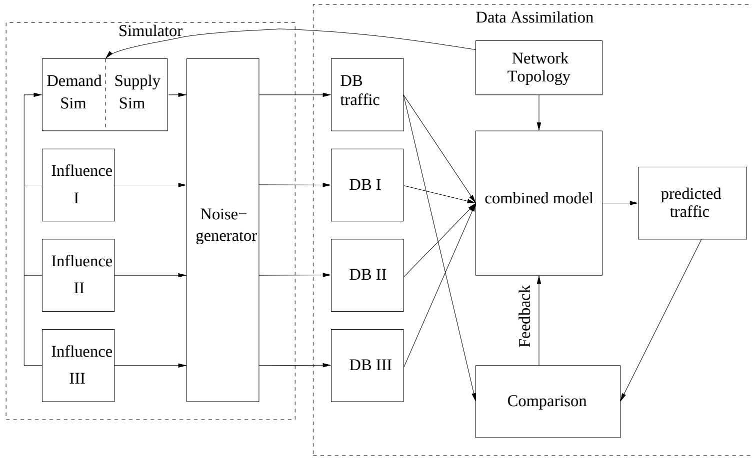


*Figure 7.* Raido simulator environment

## 5. RAIDO environment

A common complaint in research dealing with the traffic information systems is the lack of usable data. The problem is both in quantity and quality. The first problem arises from the fact that data collection usually starts at beginning of a project, which will certainly give a shortage of good data at the start of development and even at the end there is not as much as researchers would like. If large quantities of data are available it is often in an unstructured form or in a form totally unsuitable to the purposes of the project. Structuring this data requires time and therefor it will not be available for experiments at the beginning of a project. Yet even at the start of development we want to work on the knowledge discovery process, so a way was devised to have data to work with even in the early stages of the project. We have chosen for an experimental approach and are focussing initially on establishing an effective experimental environment employing simulation technology to help gathering a relevant and substantial source of data.

For the research described in this paper we have designed an environment in which a simulator generates the data needed for developing the data discovery and combination process. The simulator consists of a traffic simulator, several fabricated data sources for external influences and a noise generator. The traffic simulator is an existing program consisting of two interacting parts:

- supply contains information about the topology of the area being simulated in combination with information on lane closures due to for instance road works or accidents, which is used to determine the capacity of roads.

- demand describes the number of planned trips their origin and destination in Origin Destination Matrices

The interaction between supply and demand results in a simulation of traffic patterns. Statistics resulting from the simulation, in our case information about delays, can be stored in a database. The noise generator can be used to pollute the data-set by mutating data or leaving out some data altogether. This allows for experiments determining the minimum quality of data needed both in terms of accuracy and availability. Meanwhile we are also working to establish a source for and a database of historical data on traffic-jams. Furthermore we are currently investigating the possibility of obtaining data on external influences from the web. There are many different sources on the web which provide information on public events. There are also many web-services which offer weather forecasts. A web-crawler is in development which will obtain this information with a high level of autonomy. We will report our findings on this at a later date. When real data on either delays or influences becomes available it can replace the corresponding simulated data sources.

## 6. Discussion & Conclusion

In this paper we described our research into the next generation of Traveler Information Systems. In particular we have looked at how we can enable accurate travel advise which is based on prediction of the future state of traffic.

We described the effect of external influences on traffic and the need to model them using the data available from different sources describing these influences. We presented a modelling approach which can use data on these external influences together with current and historical data on traffic to produce a model which predicts the future state of traffic. Furthermore we have shown the experimental environment we will use for development of the data assimilation system in which the predictive model is used.

The last ten years of research in Traffic Information Systems has shown that, unless the services which are offered have a high degree of accuracy and consistency, is is difficult to create useful services. We are aware that experimental validation is key to this type of research. For instance, problems can arrive in managing computational complexity and exploiting the computational resources needed to run our proposed system in real time. The experimental environment we propose addresses this issue. We also think that developing the data assimilation system as a component that can be used outside of this domain will add much to the value of our research.

It is our belief that the approach described in this paper is the way to reach the accuracy of prediction necessary to make the next generation of Traveler Information System work.

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## References

[1] Moshe Ben-Akiva, Michel Bierlaire. Didier Burton, Haris N. Koutsopoulos, Rabi Mishalani, *Network State Estimation and Prediction for Real-Time Traffic Management*, in Networks and Spatial Economics 1: 2001 293-318, Kluwer Academic Publishers

[2] Everett M. Rogers, *Diffusion of Innovations, fourth edition*, New York:Free Press,1995.

[3] Philip Parker, *Aggregate Diffusion Forecasting Models in Marketing: A Critical Review*, International journal of forecasting, 10, 1994, p. 353-380.

[4] Geleyn R. Meijer, Jacco Samuels (CMG Unwired Concepts) and Frank Terpstra (University of Amsterdam), *Modeling user acceptance and technology adoption: is there a case for value added services?*, ITS World Conference on Intelligent Transport Systems, Chigaco october 2002.

[5] I. Foster, C. Kesselman, S. Tuecke, *The anatomy of the Grid : Enabling scalable virtual organizations*, The International Journal of Supercomputer Applications, 2001.

[6] H. Afsarmanesh, R.G. Belleman, A.S.Z. Belloum, A. Benabdelkader, J.F.J. van den Brand, G.B. Eijkel, A. Frenkel, C. Garita, D.L. Groep, R.M.A. Heeren, Z.W. Hendrikse, L.O. Hertzberger, J.A. Kaandorp, E.C. Kaletas, V. Korkhov, C.T.A.M. de Laat, P.M.A. Sloot, D.Vasunin, A. Visser and H.H. Yakali. *VLAM-G: A Grid-based virtual laboratory*, in Scientific Programming (Special issue on Grid Computing), 10(2), pp. 173-181, Ronald H. Perrott and Boleslaw K. Szymanski editors. IOS Press, 2002, ISSN 1058-9244.

[7] Daley, R., 1991: *Atmospheric Data Analysis* Cambridge University Press ISBN: 0521458250

[8] J. Gehrke, F. Korn, D. Srivastava. *On Computing Correlated Aggregates Over Continual Data Streams*, SIGMOD 2001, Santa Barbara, CA, 13-24.

[9] R. E. Kalman. *A New Approach to Linear Filtering and Prediction Problems*, in Transactions of the ASME–Journal of Basic Engineering, vol 82, Series D, pages 35-45, 1960.

[10] Bogaert P. and D'Or D. *Estimating soil properties from thematic soil maps : the Bayesian Maximum Entropy approach.* in Soil Science Society of America Journal 66(5): 1492-1500, 2002.

[11] Eelco Herder and Betsy van Dijk. *Personalized adaptation to device characteristics*, Second International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems, May 2002. Springer LNCS 2347, pp. 598-602