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Model and Computation of traffic Resilience

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ABSTRACT

At many times we observed disturbances of traffic flow on highways. This may be caused by traffic accidents, bad weather conditions, road maintenance or rush hours. The Road Traffic Management takes many rules and regulation, to make road sections more robust to disturbances and improve the recovery from disturbances in traffic flow (traffic resilience). To study the effect and impact of these rules and regulations assessment models of traffic resilience was needed. In this paper, we designed and tested such an assessment model. The model is inspired by the well-known Resilience Triangle. The assessment of traffic resilience was based on measurements of the speed of traffic flow on highways. Neural Networks were used to model and smooth recorded speed data. The Traffic Resilience model has been tested on real life data.

CCS CONCEPTS

• **Information systems** → Information systems applications; Decision support systems; Data analytics; • **Applied computing** → Computers in other domains; • **Computing methodologies** → Artificial Intelligence.

KEYWORDS

Traffic Resilience, Neural Networks, Resilience Triangle

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1 INTRODUCTION

The maximal speed of traffic has been limited to 100-120 km on the Dutch Highways. But on many occasions, we observed a reduction of the traffic speed. This may be caused by the following reasons:

- Bad weather conditions. During heavy rainfall or icy conditions car drivers reduced their speed. Warning signals advice car drivers to reduce their speed and keep their lane.
- Traffic incidents. During crowdy traffic conditions or bad weather, many incidents occur. The speed of the traffic flow shows a (sharp) reduction and shock wave behavior.
- The condition of road segments. Some road segments need reconstruction or repair and don't allow fast driving. These road segments are more sensitive to accidents.

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It is important that the traffic flow recovers from disturbances and returns to its stable situation as soon as possible. But it is also important that road sections keep their stable position. It proved that some road segments are better equipped to keep their stable position (homeostasis). In this paper traffic resilience was considered as the ability of a road section to resist and recover from disturbances in traffic flow. It is not always possible to develop special research experiments to investigate the traffic resilience of road segments. In this paper we developed a continuous traffic resilience surveillance program using available data from measurements of traffic flow.
In our experiments, road segments were selected because of occurrence of congestion caused in the rush hours. The traffic management toke many measures to solve the congestion as soon as possible, such as warning signals on DRIPS, traffic signs and the use of traffic lights. The effects of these measurements were regularly checked to see if the traffic resilience on these road segments has been changed. We proposed a new model of resilience control on this special road segments.
Our resilience model is based on the speed of traffic flow. Speed of cars can be measured by wires in the road surface. A network of wired networks has been installed along the highways in The Netherlands. The database of recorded traffic flow, annotated by weather conditions, time, date, season and information from the emergency services, provided a testbed for our resilience research. Neural networks were used to compute the traffic flow on special road segments based on recordings of traffic flow for selected days. The results were compared with the average traffic flow computed over the whole year. Significant differences could be detected by visual inspection.
The topics discussed in this paper are the following. In section two we present related work. And in section three we discussed our Traffic Resilience model. In section 4 we used Neural Networks models to smooth the recorded traffic flow data and to predict traffic flow and upcoming traffic incidents.

2 RELATED WORKS

TRAIL is the Netherlands Research School on TRAnsport, Infrastructure and Logistics. Six Dutch Universities, including Delft University of Technology and the independent research organization TNO are members of TRAIL. Traffic Resilience is a research topic for many years. In [1] an innovative model of resilience of road sections was developed by Snelders et al. In this paper we developed a computational model and applied it to traffic flow data. Snelders and her colleagues discussed also the concepts' reliability, vulnerability, robustness, related to resilience.
In [2] Vink et al. developed a new Incident Management System using AI technologies to improve communication around incidents. Distributed Blackboard Systems were used to store and distribute observations and communication of first responders using their smart mobiles. A multiple Agent System was used to update the

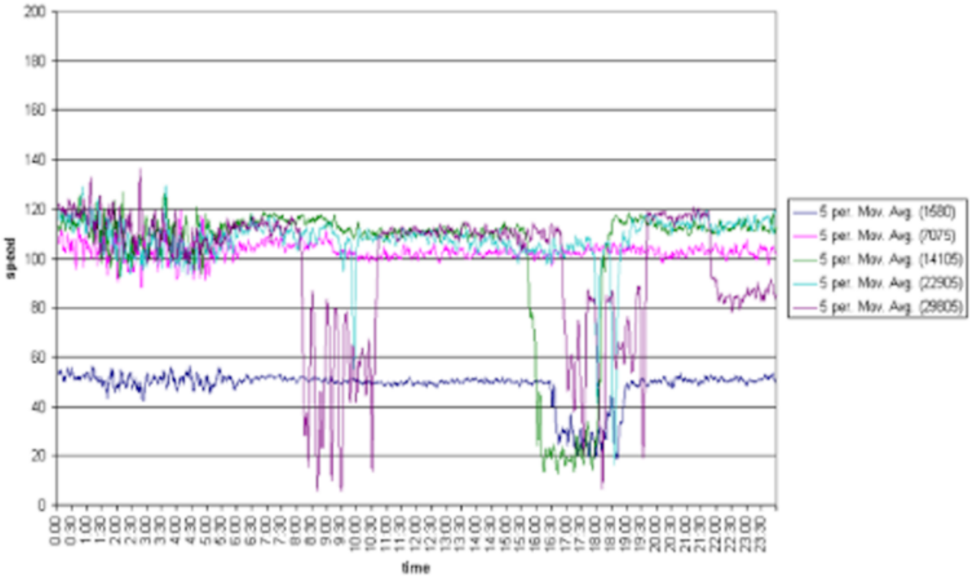

Figure 1: Graph of average speed on 5 locations.

Blackboard Systems, to distribute the information and to alarm involved first responders. By simulation experiments, it was shown that the traffic resilience of the new system was improved. The authors of [3] put a focus on agents in their research on resilience. They computed resilience along Dutch roads using simulation tools and an agent-based traffic model. Both AI-topics play an important role in our research.

The authors of [4], Jacobs et al. researched the prediction of averaged traffic speed on highways using Artificial Neural networks. She processed a huge database of traffic speed data along the Dutch Highways recorded by the company TENUKI. This company used the huge network of wires in the surface of the roads and MONICA a communication network to record traffic data along the highways. Our work on traffic resilience was partly based on this research.

Recently traffic speed is computed using smart phones of car drivers and special routing systems as TomTom. To record data of car drivers' permission is needed. That is the main reason that the system MONICA is still used in our research [5–8].

The authors Galderisi et al. [9] discussed the resilience of 100 cities. The Rockefeller Foundation launched a 100 Resilient City Initiative. They focused on multiple shocks and stresses, including climate change and the reaction of 100 cities. There was a special focus on a comparison between the cities Rome and Athens. In the paper the main strengths and weaknesses are described and to cope with one of the current challenges, the traffic resilience in cities.

The authors of [10] presented in 2018 the start of urban resilience. The Rockefeller Foundation launched the 100 Resilience Cities program providing an enormous boost to this resilience program. Global norms were defined and assessment tools were created, rendering urban resilience from a technical and management perspective.

In [11] the authors stressed, that there is an enormous interest of researchers in resilience in urban mobility. But in the current literature there is a lack of application and computation of resilience. In their paper the authors discussed a methodology to assess resilience in urban mobility. They used a commonly available dataset of origin-destination trips. The trips were classified according to their level of resilience. Two urban areas in Brazil were used as testcases.

In paper [12] measures of urban highway network resilience were discussed consistent with the concept of resilience triangle. The involved features are queue length, link speed, link travel time, frontage road delay and detour route delay.

3 MEASURE OF TRAFFIC RESILIENCE

Traffic Resilience in this paper is about prevention and recovery of disturbances of traffic flow. A good measure of traffic flow is the average speed of cars on highways. The measurement of speed of cars shows a lot of fluctuations (see Figure. 1). This is not only caused by the fact that different types of cars as lorries, autobus and passenger cars drive with different speed, caused by traffic limitation but also by the fact that distances between successive cars show a lot of variation. From Figure 1, we can see that the average speed on Dutch highways varies usual between 100-120 km. By traffic measurements it can be limited to 50 km. We observed that during rush hours in the morning and afternoon, there is a reduction of speed, usually as successive shockwaves. In case of a traffic accident in the right part of Figure 1 we observe a sharp drop of speed, which keeps low for some time and then recovers again. The degree of disruption of average traffic speed is represented by the valley between onset and offset of dropping average speed. In ideal situation it can be modelled by a triangle (Figure 2). But usual the valley shows a more complex behavior of the dropping of

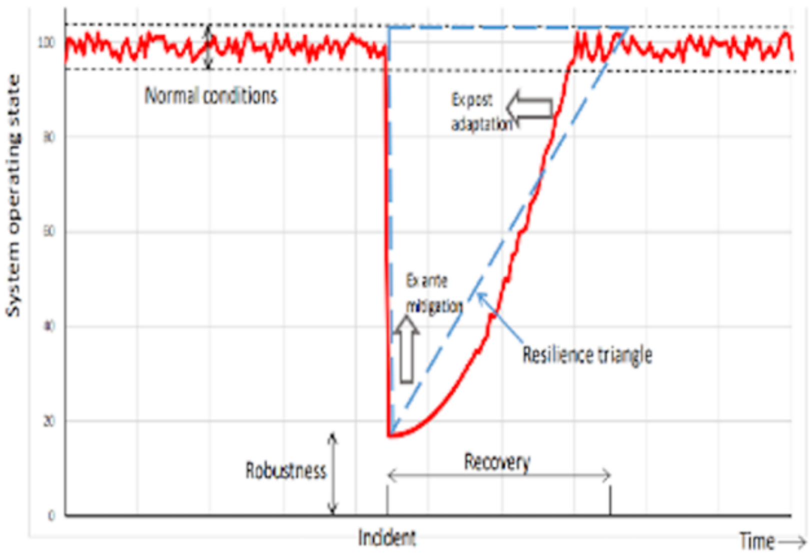

Figure 2: Resilience Triangle (blue) and average speed (red).

average speed. The graph including fluctuations in traffic speed and should be smoothed. This can be done by applying Artificial Neural Networks, discussed in the next section. A first approximation of traffic resilience is the area of the graph between onset and offset. Sometimes a recovery of traffic speed disturbance is followed by a next dropping of speed caused by an incident or shockwaves.

4 MODELLING TRAFFIC SPEED BY NEURAL NETWORKS

From the graphs in Figure 1 we can see that average traffic speed shows a stochastic, noisy behavior. During the rush hours the graphs showed a dip within some time interval. The graph varied for different days. To model the graph, we could use different function approximation technologies. We preferred to use Neural Networks which was successfully used in one of our studies [4]. We used a feedforward network trained with the Backpropagation algorithm (see Figure 1). To train the Neural Network we used recorded data of traffic speed on the highway A12 in the Netherlands. The traffic speed measurements were annotated with time, weather, location, day of the week, season. For the point near Zoetermeer (location 14105) the number of training samples is 127450 and for Gouda (location 29850) this number is 127314.

In our first experiment we trained a Neural Network of topology 2-n-1 with two input parameters time and data da(t) and one output parameter ox(t) (see Figure 3) using Neural Network toolbox in MATLAB. From the theory of ANN several formulas are available to assess the number of hidden neurons. We did some experiments and found that 2-5-1 was the most optimal topology. As usual 90 % of the data was used for training and the remaining 10% for testing. In a first experiment we trained a Neural Network of topology 2-5-1 and test it on the recorded data on Tuesday 11-12-2002. We computed also the average speed over all Tuesdays in 2002 and

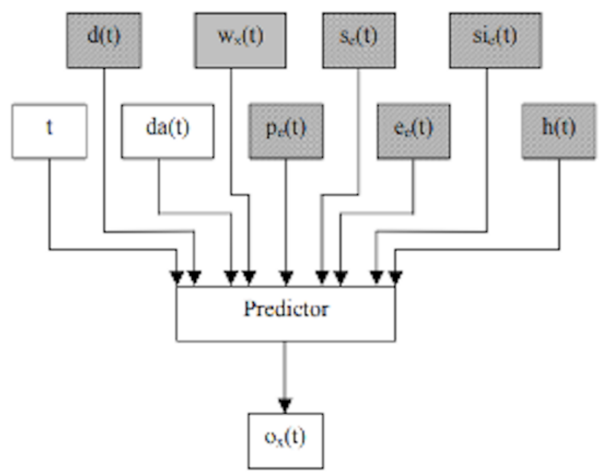

Figure 3: ANN model of average speed given time t and date da(t).

used this as a benchmark. Both results of training and computation are displayed in Figure 4. By visual inspection it is possible to see if the recorded data on 11-12-2002 differ significantly. We can also compute the surface of the valleys in Figure 4 displayed by the yellow and magenta line.

The computation of the traffic resilience was of special interest on days when existing traffic measures are out of action or when new measurements are introduced and new traffic regulation technology has been installed.

In Figure 4 we display the average traffic speed around the city of Zoetermeer, the average traffic speed of all Tuesdays in the year

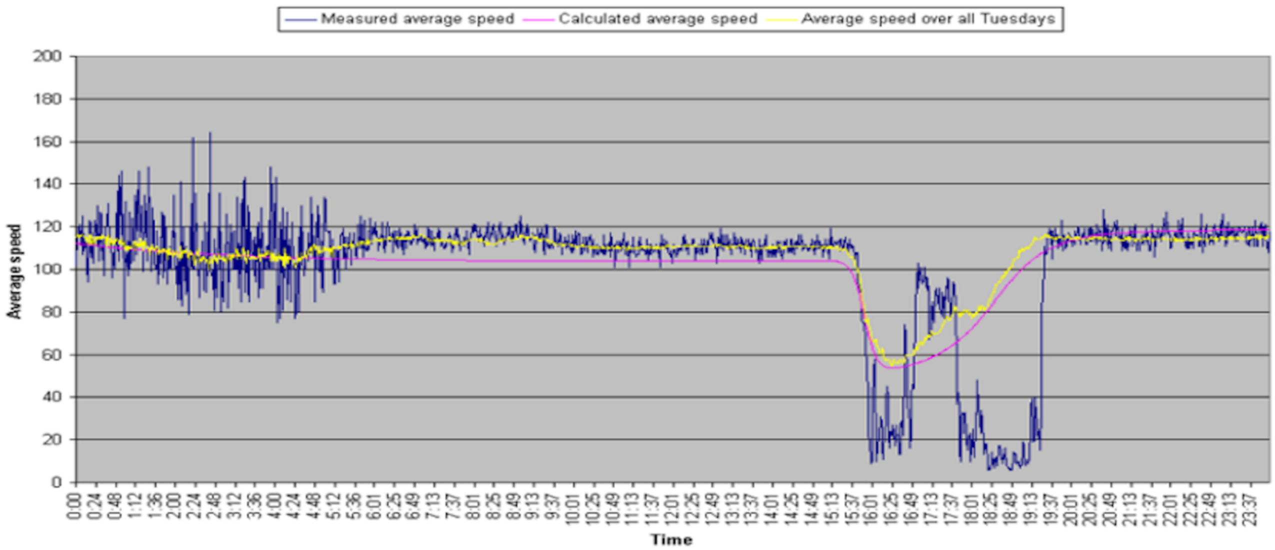

Figure 4: Measured, calculated and computed average speed on Tuesday 11/12/2002.

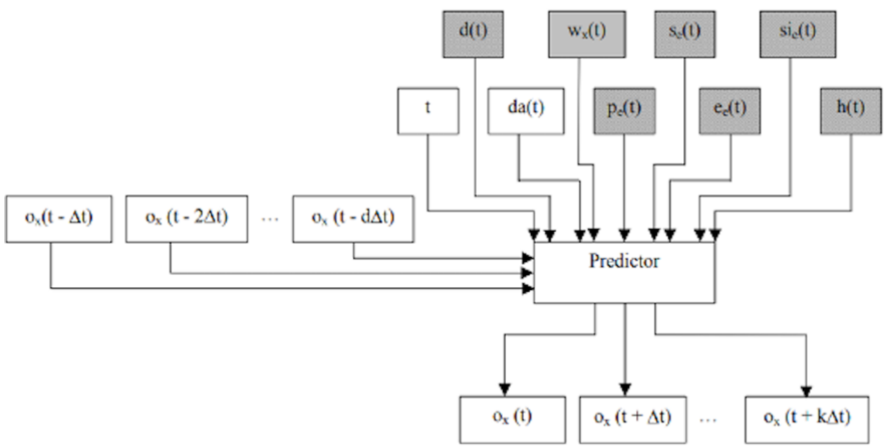

Figure 5: Predicted speed predicted speed ox(t+k∆t), day of the week d(t), weather wx(t), place of event pe(t), start, end event se(t), ee(t).

2002 (yellow line) and the results of training an ANN of topology 2-5-1 and tested on the data recorded on Tuesday 11-12-2002 (Magenta line). We observe that on that day the two lines are close to each, so the traffic resilience didn't change on the day on that road segment. We see also that the first valley of traffic congestion is followed by a second valley and that ANN is not able to follow the recorded traffic data. More advanced topology of ANN is needed as we will see in the next section.

From Figure 4 we can see that the graph of average speed shows a stochastic behavior. After the smoothing operation by ANN, we observe some trends during the rush hours and traffic incidents. Taking the data of the whole year into account we computed a template of the average speed (yellow line in Figure 4). But the variation of traffic speed may vary enormously during bad weather conditions or special accidents. These effects are smoothed away by taking the average. Improved forecasting traffic speed over a short time interval is important to take appropriate actions. Information about upcoming or reducing queues can be displayed on DRIPS above the highways. Adapting speed signals have a significant impact on the speed of the traffic flow.

To improve the forecasting by taking the average speed we used again ANN. We selected the data corresponding with congestion during the rush hours and incidents over the year 2002. The architecture of the used ANN is displayed in Figure 5. Neural networks were trained on the recorded data. It proved that ANN n-5-m was able to forecast traffic speed.

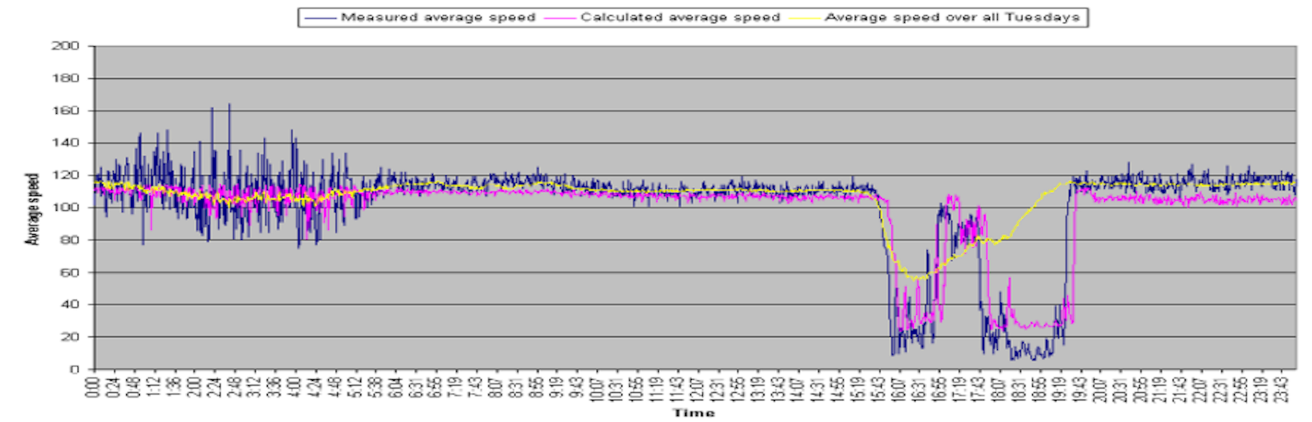

Figure 6: The average speed on 12th of November 2002 near Zoetermeer with the 5-1-4- topology 40 minutes ahead.

The number of trainings examples for the point near Zoetermeer (14105) and the point near Gouda (29805) are respectively 118584 and 119311.

5 FORECASTING TRAFFIC SPEED BY NEURAL NETWORKS AND RESILIENCE MODELS

To predict traffic speed more advanced ANN are needed. After some testing the topology 5-1-4 with time series on the input and output gives optimal result. From Figure 6 we can see that this type of Neural Network is able to predict the traffic speed 40 minutes ahead. This is especially important to assess the onset and offset of the valley of congestion. Road managers are able to take measurements to reduce congestion in time.

As stated before, the road segments with regular traffic congestion were selected to compute and compare traffic resilience. After traning the network on traffic data of the whole year, a testday was selected and the output of ANN on that day computed and displayed. The successive graphs of the testday provides an overview of the traffic resilience on that road segment and the displayed graphs can be used to assess if the resilience is changing. In that case further investment takes place in the Traffic Control Centers.

6 CONCLUSIONS

The goal of this paper was to design a computational model for traffic resilience on road segments. These road segments showed regular traffic jams in the rush hours. We used ANN to smooth the real-life recorded data and to forecast traffic speed. By comparing the computed output of ANN on a daily basis with the yearly average of traffic speed on that road segments, we could detect changes in traffic resilience by visual inspection. The differences in resilience can also be computed by using the Resilience Triangle. The findings are demonstrated with some graphs using recorded and computed traffic speed on the specific road segments.

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