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Decision support system for variable speed regulation

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ABSTRACT

Recommending appropriate speed limits for roads is important for road authorities in order to increase traffic safety. Nowadays, these speed limits can be given more dynamically, with digital speed regulation signs. The challenge here is input from the environment, in combination with probabilities for certain events. In this paper, we present a decision support model based on a Dynamic Bayesian Network (DBN). The purpose of this model is to predict suitable velocities on the basis of weather data and knowledge about traffic density as well as road maintenance activities. The DBN principle of using uncertainty for the involved variables gives a possibility to model the real conditions. This model shows that it is possible to develop automated decision support systems that take uncertainties in account, for variable speed regulation.

Keywords: Decision Support System, Variable Speed Limits, Dynamic Bayesian Networks.

1 INTRODUCTION

Variable speed regulation systems have been deployed at many sites in Sweden. Four different motives for adjusting speed limits have been tested, traffic conditions, weather situation, intersecting traffic and the presence of vulnerable traficant's. It has been shown that compliance with the posted speed is very good and that the accident rate has decreased in areas where these systems have been installed [1]. Previous research regarding weather-controlled speed limits in Finland has also shown that these systems increase traffic safety by decreasing mean speeds and speed deviation [2].

An important part of the weather-driven variable speed project is a proper model that indicates the appropriate speed limits according to prevailing road weather conditions. Many of the current models in use for determining road conditions rely on current road status and on road weather prognosis for the prediction [3]. Some research has though been done where artificial intelligence has been evaluated in order to improve forecasts [4]. In the simplified model proposed here, the predictions are made on the probability of certain events, but the road weather prognosis is however not taken in consideration. The purpose of this paper is to present a way of developing a model that takes the uncertainties in account when combining weather information and knowledge about current road condition when estimating a suitable speed limit. The proposed model is, as said above, somewhat simplified to enable an easier understanding of the principles. A model intended for implementation in real situations requires additional input sources to comply with real world situations.

First generation expert systems assigned each proposition a numerical measure of uncertainty which were then combined to get a value of uncertainty. This approach has proven to give unpredictable and counterintuitive results why the current Artificial Intelligence (AI) methods characterize the formulas under consideration and summarizes them in order to get a truth value for the probable outcome. A common AI method of handling uncertainties is by using Bayesian networks. Bayesian networks provide formalism for reasoning about partial beliefs under conditions of uncertainty. This means that propositions are given numerical parameters that describing the belief provided some knowledge. The parameters are then combined according to the rules of probability theory [5].

The model described in this paper is developed as a Dynamic Bayesian Network (DBN). The model contains time dependent choice nodes with evidence, using Markovian prediction as described in [6]. Here we use a first-order Markov process, which means that the developed model assumes the current state to only depend on the previous state. The dynamic Bayesian network principle of using uncertainty for the involved variables gives a possibility to model the real road status conditions. In real conditions there is some uncertainty when forecasting road conditions and this uncertainty can be handled by using a DBN model. For example, even if a prognosis states that the temperature will stay above 0, there is a possibility that it will drop below zero hence causing severe road conditions. This uncertainty should be dealt with a better way than what is done today.

2 MATERIALS AND METHODS

There are two factors that play a direct role in a simple model concerning speed regulations; this factors are the density of traffic and the friction of the road surface. Traffic density can be sensed by counting passing by cars. Friction is more involved, and depends on different factors, as can be seen in Figure 1. We are using discrete probability distributions for the five independent stochastic variables. The distributions can be seen in Figure 1. The chosen probability distributions are not empirically verified, we assume them to be true for this research purpose. The road friction depends on the road surface status, which is influenced by ice and frost. Those two in return can be stochastically inferred from the collected sensor data; air temperature, air humidity, road temperature, precipitation, and information about de-icing tasks. The frost and ice distributions are in themselves affected by the study site; why we differentiate very coarse between Norrland and Gotaland (these are regions in northern and south of Sweden). We do that by defining Norrland or Gotaland as evidence for the *Area* chance node.

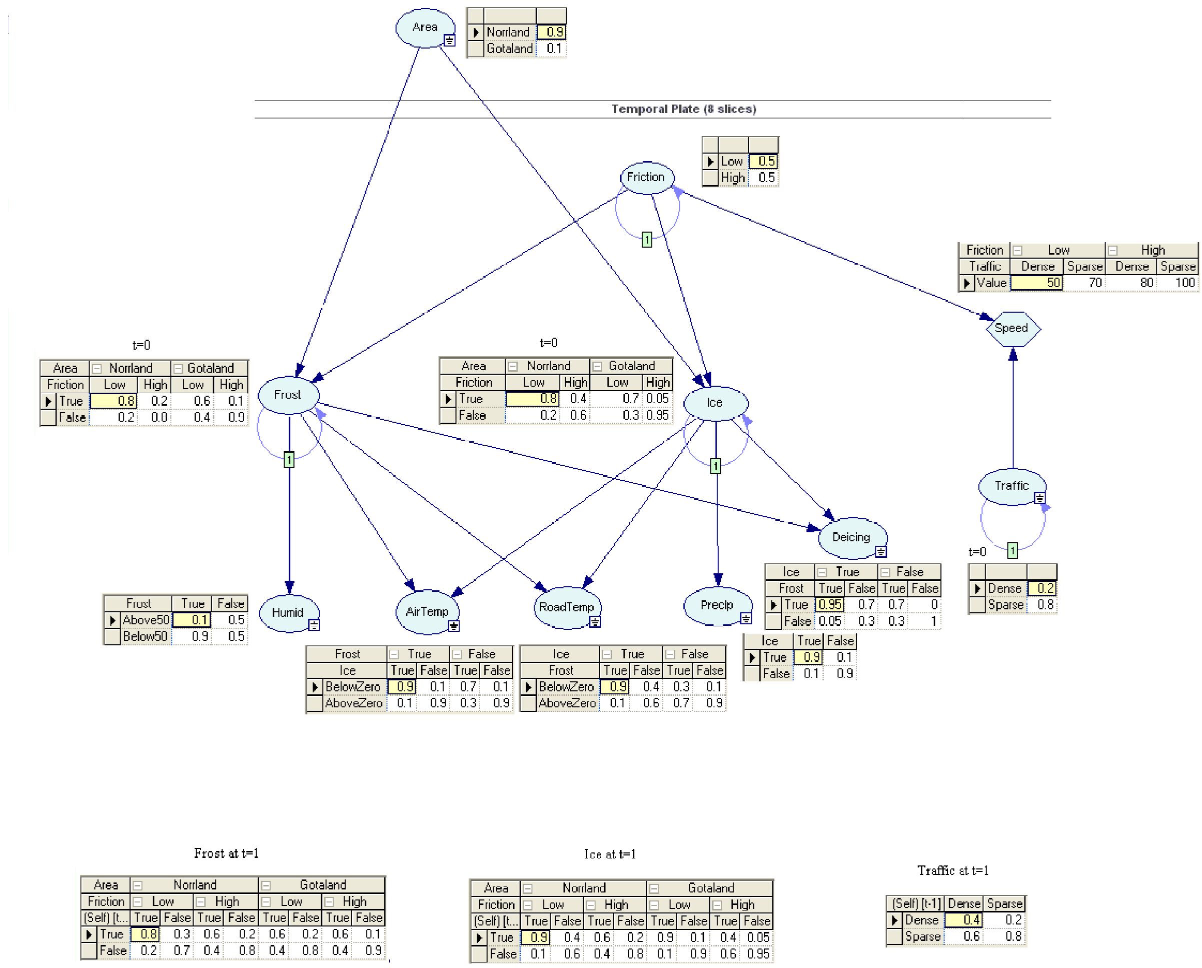

Figure 1. The Dynamic Bayesian Network for the speed regulation problem. Area is a static node that will be initiated at model simulation startup. The nodes Friction, Frost and Ice are intermediate nodes that will be updated during the model simulation. The nodes Humid, AirTemp, RoadTemp, Precip, Deicing and Traffic are sensor or observation nodes that will be updated during the model simulation. The Speed node is a utility function that gives the ouput of the network as a recommended speed.

Due to the fact that we have access to evidence sensors for air temperature, humidity, road temperature, precipitation, de-icing tasks, and traffic density, and since the problem is time dependent, we decide to model the chance nodes frost, ice, friction and traffic according to Markov prediction, and integrating the time steps.[6] Thus, a Dynamic Bayesian Network (DBN) was created with nodes defined to comply with the assumed road status situation, see Figure 1.

2.1 Static node

The *Area* node is static, which means that it will not be changed from the other nodes during the simulation of the model. The probabilities for Norrland (northern Sweden) is set higher than Gotaland (southern Sweden) because of the longer winters and colder temperatures. These two selections can also be used as an evidence to adapt the model to different regions. The latter usage is preferred as the previous method would give the obvious result that Norrland is more affected by Frost and Ice.

2.2 Intermediate nodes

Intermediate nodes are defined as updated from other nodes. These nodes are thus not directly measured, but their updated probability values can be studied during the simulation.

Friction is an intermediate node, as it will be updated by other nodes during the simulation. The initial probabilities for low or high friction are both 0.5 which should be reasonable when we do not have any knowledge about the current road status. At time t=1 we take in consideration the previous state and assume that if there was a low friction there will probably be a higher risk (0.6) that it is still present. On the other hand, if there is a high friction, we assume that it will be quite certain that it will remain (0.9).

Frost is also an intermediate node and the probability of frost is high when the friction is low, and even higher when we are in the area of Norrland. The Frost at time t=1 will consider Frost present at t=0 and thus have a high probability that the frost is still present.

Ice is an intermediate node similar to *Frost* but *Ice* is more probable when the Friction is low and when we are in Norrland.

2.3 Sensor or observation nodes

In the DBN modelled here there are also sensor nodes, sometimes called observation nodes. In this case we define the sensor nodes as deriving from commonly used physical sensors, and we define observation nodes as data retrieved from maintenance personnel or other, for RWIS systems, uncommon sensor types.

The sensor node *Humidity*, has the states above 50% Rh and below 50% Rh. A humidity above 50% is related to frost as a high content of water in the air is more likely to cause water to sublimate on the surface when the temperature drops.

The sensor node *AirTemp* describes the air temperature. An air temperature below or close to zero is required to get frost or ice. Thus, the probability for air temperature below zero is high when frost and/or ice are present.

The sensor node *RoadTemp* describes the road temperature. A road temperature below zero is required to get frost or ice. Thus, the probability for road temperature below zero is high when frost and/or ice are present.

The sensor node *Precip* describes the precipitation. Precipitation is requirement for ice on the road. Ice is formed from snow or rain falling onto a cold surface. So, having ice, there is a high probability of precipitation.

De-icing is an observation node that indicates that de-icing tasks are done on the road surface.

Traffic is an observation node that indicates the traffic intensity. The assumption is done that the traffic is more often sparse than dense, therefore, the probability for dense traffic is low (0.2).

2.4 Utility function

In order to get a usable output from the DBN, a utility function is created. The utility function gives as output a decision of which speed limit to recommend based on road friction and traffic density. The speed limit recommendations can be seen in the table above the *Speed* utility node in Fig 1. (e.g., a recommendation of 50 when friction is low and traffic is dense, and 70, when friction is low and traffic is sparse)

2.5 Evidence

The DBN needs evidence, which is the real observed situation for the prevailing parameters. In this model evidence is set for each node at each time step. In this model it is assumed that data is collected every 10 minutes, and that evidence of the current situation is also collected at the same time interval. An integration of the evidences every 10 minutes is reasonable because weather and traffic is very dynamic and can change within this time space. The evidence values used in this model can be seen in Figure 2 to Figure 7.

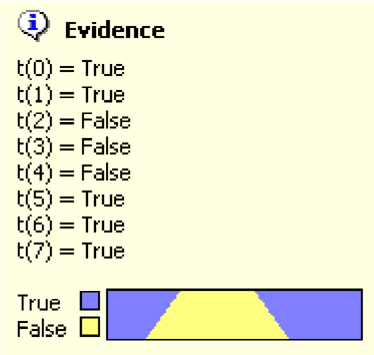

Figure 2. Evidence for the air temperature sensor node *AirTemp*.

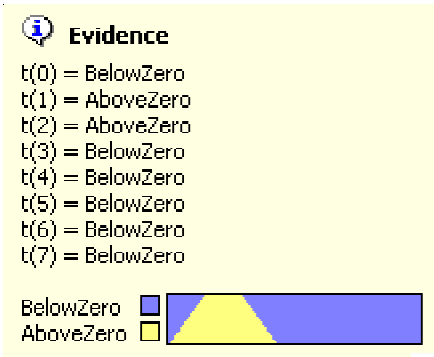

Figure 3. Evidence for the de-icing observation node *Deicing*.

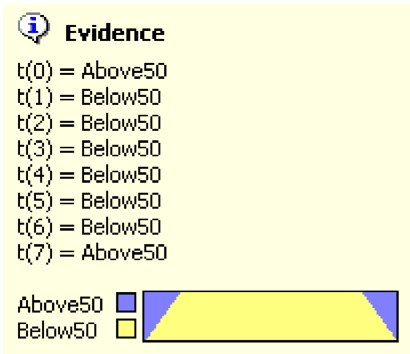

Figure 4. Evidence for the humidity sensor node *Humid*.

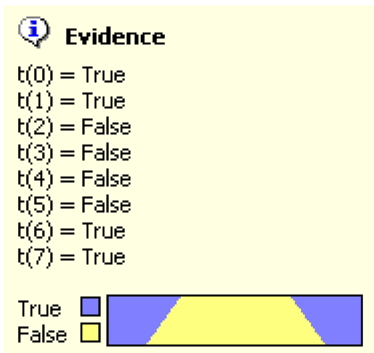

Figure 5. Evidence for the precipitation sensor node *Precip*.

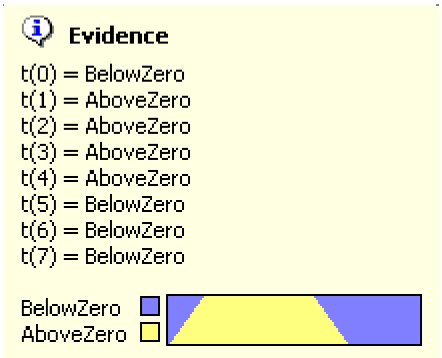

Figure 6. Evidence for the road temperature sensor node *RoadTemp*.

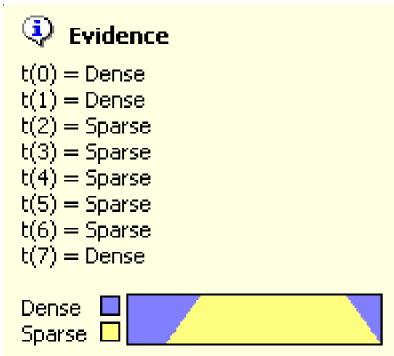

Figure 7. Evidence for the traffic intensity observation node Traffic.

2 RESULTS

The model was run for 8 timesteps, with inputs from each node as in Figures 2 to Figure 7. Intermediate results from the nodes *Frost*, *Ice* and *Friction* are shown in Figure 8, Figure 9 and Figure 10. The values for these intermediate nodes can be seen to vary fairly smoothly which should comply with normal behaviour on the road.

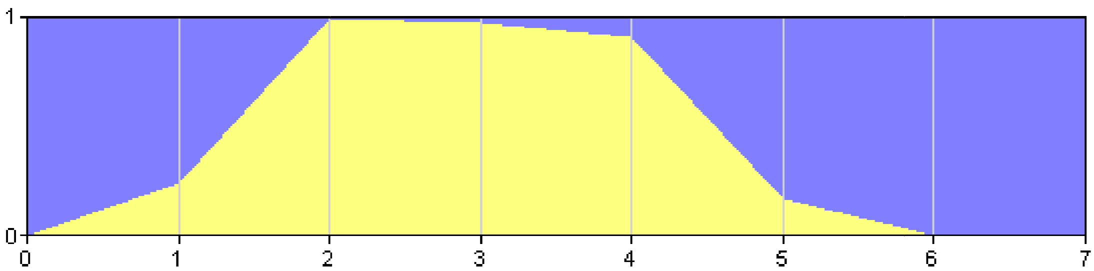

Figure 8. Intermediate probability trajectories from the chance node *Frost*.

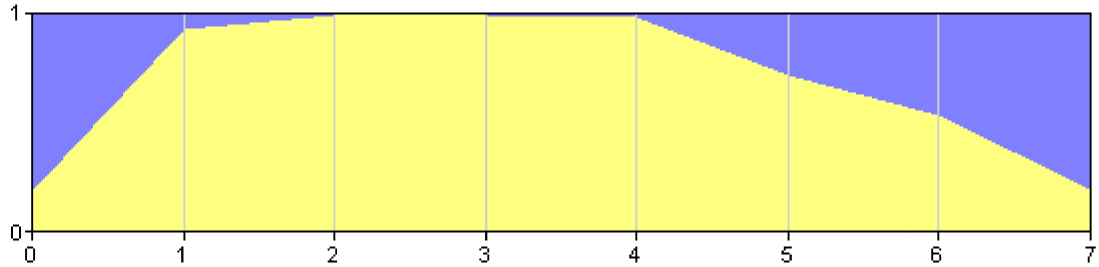

Figure 9. Intermediate probability trajectories from the chance node *Ice*.

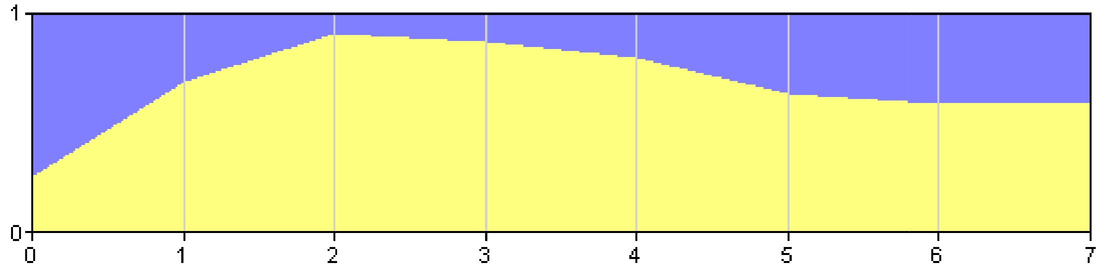

Figure 10. Intermediate probability trajectories from the chance node *Friction*.

The output from the Speed utility node is a trajectory of recommendations for the respective time steps, see Figure 1. The curve shows that the speed limit is not categorised to the specific speed limits used as input, which may be expected, but the speeds were more smoothly adjusted. This smoothing is a result from the regression made from the node inputs.

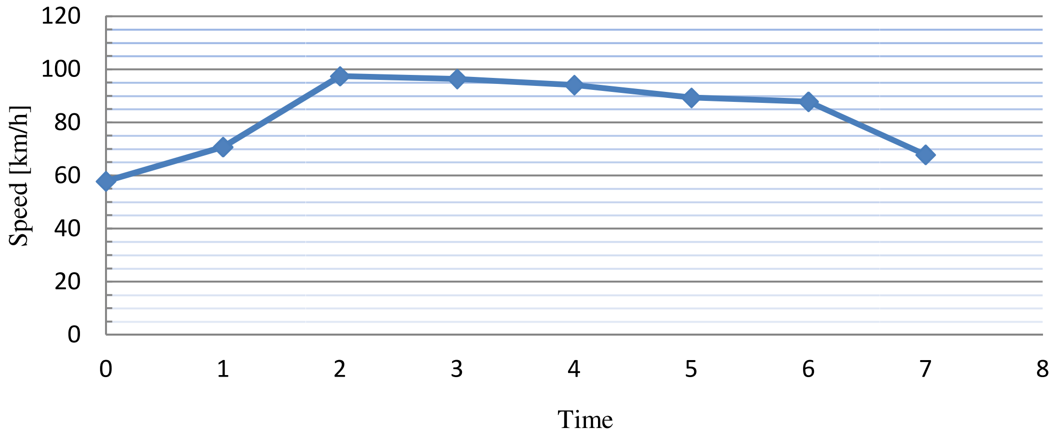

Figure 11. The recommended speed limit over the 7 time steps, as a result of running the DBN.

2 CONCLUSIONS

A Dynamic Bayesian Network (DBN) was constructed with the aim to suggest suitable speed limits for variable speed signs during icy road conditions, taking uncertainties of the monitored road status inputs in account. The resulting speed limits were a continuous number that could vary from the lowest to the highest speed limit set in the initial settings. For practical usage, the next higher speed limit could be showed on the speed limit signs to avoid displaying too low speed limits that could be offensive for drivers, thus making the automated speed regulation less trustworthy.

The use of a first-order Markov process in this model implies that only the previous state affects the current state. Possible improvement of the model performance by using higher order Markov processes where earlier states affect the current state need to be investigated. In this model only the most common sensors installed in various RWIS applications are used. If the model should be used in a specific RWIS network, the unique sensors for this

RWIS network should be added as they may improve the model performance. Also, meteorological forecasts should be considered as a valuable input for this model. Today a lot of the road maintenance tasks are triggered by the forecasts, which indicates the value of integrating forecast data as a sensor node for the model. Another assumption made in this model is that icy roads depend on a preceding precipitation. This is not entirely true, because moist may deploy on the road surface due to condensation of hot air on a cold surface, and thus lead to icy road conditions.

The limitations of this model should of course be handled in model candidates intended for practical usage. This study has been simplified because the aim was to present a method of using DBN that may improve the performance of existing and future speed regulation systems when taking uncertainties in account. A more detailed model is therefore yet to be developed for practical implementations.

The conclusion from this research is that the use of DBN gives benefits compared to the simplified methods in use today by the Swedish Transport Administration. The benefits are a model that takes previous states of road conditions and their uncertainties together with previous suggested speed regulations in account when proposing updates of the speed limits. This will make the DBN model more responsive to the natural changes of the road weather and current speed regulation situation compared to the models in use today.

ACKNOWLEGEMENTS

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5 REFERENCES

[1] Trafikverket, "Variabel hastighet på väderstyrda vägar - tillämpningsrapport," Teknikavdelningen, ed., Trafikverket, 2008.

[2] P. Rämä, "Effects of Weather-Controlled Variable Speed Limits and Warning Signs on Driver Behavior," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 1689, no. -1, pp. 53-59, 1999.

[3] J. Bogren, and T. Gustavsson, "Modelling of local climate for prediction of road slipperiness," *Physical Geography,* vol. 10, no. 2, pp. 147-164, 1989.

[4] K. Sirvio, and J. Hollmén, "Spatio-temporal Road Condition Forecasting with Markov Chains and Artificial Neural Networks. Hybrid Artificial Intelligence Systems," Lecture Notes in Computer Science E. Corchado, A. Abraham and W. Pedrycz, eds., pp. 204-211: Springer Berlin / Heidelberg, 2008.

[5] J. Pearl, *Probabilistic reasoning in intelligent systems : networks of plausible inference*, San Francisco, Calif.: Kaufmann, 1998.

[6] S. J. Russell, and P. Norvig, *Artificial intelligence : a modern approach*, Upper Saddle River, N.J: Prentice Hall, 2003.