AN INTEGRATED DYNAMIC TRAFFIC ASSIGNMENT- BAYESIAN BELIEF NETWORKS METHODOLOGY TO ASSESS TRAFFIC SAFETY

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ABSTRACT
Traffic conditions significantly affect drivers' behavior that constitutes one of the principal causes of road accidents. Being able to accurately predict traffic conditions significantly improves the assessment of accident risk. Traditional approaches to traffic flow analysis use static representations of the road system and as such have limited accuracy. Dynamic Traffic Assignment (DTA) approaches better utilize temporal aspects of such system (where and when to travel on the road network) to produce better predictions. The work presented herein integrates two mature methodologies namely simulation-based DTA and Bayesian Networks (BN) to address this problem. The former is widely used in transport modeling to predict driver's travel behavior while the later constitute a powerful artificial intelligence technique that predicts effects given prior knowledge and input evidence in uncertain settings. The integration of BN with the DTA-based simulator, Visual Interactive Systems for Transport Algorithms (VISTA), provides the framework for improved safety evaluation of road networks and future planning.

Keywords: Road Safety, Dynamic Traffic Assignment, Bayesian Networks

INTRODUCTION

Road accident statistics in Europe stress the need for more systematic mechanisms for accident analysis and prediction. According to the World Health Organization (WHO 2005) road accidents constitute the third most frequent cause of death for people of the age 17-29. Given the current trends the accident fatalities are projected to become the second most common cause of death in 2020. Given this evidence, the current road safety management and forecasting practices need to improve. Forecasting is a field of tremendous importance that enables prediction of road safety performance given known, unknown and observed information.

Due to their nature, road networks constitute complex dynamic and uncertain systems influenced by human, technological and environmental aspects. Given this, one of the best ways to understand the causes of road traffic accidents is to develop various models capable of identifying significant factors related to human, vehicle, socio-economic, infrastructural, and environmental properties. Hollnagel (2004, 1998) classifies complex systems' accident models in three core categories, the sequential, epistemological and systemic. The first describes accidents as sequence of events that occur in a specific order. The second uses the metaphor of a disease that describe outcomes as a combination of factors, some manifested, some latent, and finally, systemic models describe performance of a system as a whole (Systems Theory). With regards to road accidents, there are two broad categories of accident analysis methods, the qualitative and the quantitative. The former, despite its limited use, it plays an important role in the process of accident analysis, modeling and forecasting. On the other hand, quantitative methods are more widely used and are classified into two principal groups: Time-series forecasting and Causality-based forecasting.

The accident analysis approach proposed herein combines a causality-based with a systemic technique namely, BN and Traffic simulation. The former is popular in the Artificial Intelligence domain and is based on the concept of Bayesian probability. BN provide a language and calculus for reasoning under uncertainty (Pearl 2000). They are useful for inferring probabilities of future events, on the basis of observations or other evidence that may have a causal relationship to the event in question.

The second component of our approach is a road traffic simulator using DTA. Simulation-based DTA models constitute an innovation in traffic simulation that departs from the traditional static analysis of traffic phenomena, namely static traffic assignment (STA) (Peeta and Ziliaskopoulos, 2001). DTA use traffic simulation to replicate complex traffic flow dynamics especially for signalized systems where the vehicle and signal interactions are difficult to model analytically. This enables dynamic control and management systems to anticipate problems before they occur rather than simply reacting to existing conditions. DTA has evolved rapidly over the past two decades. This advancement has been fueled by the needs of application domains ranging from real-time operations to short term and long term planning. DTA models constitute a natural evolution in the transportation domain and are expected to become mainstream when their inherent assumptions are fully realized with advanced mathematical modeling that will overcome to a greater extent their high complexity (Sisiopiku et al, 2006). DTA evolved from the static assignment approaches that assume that traffic flow is static and independent of time. Hence, one of the main features of DTA models is the dynamic analysis of road networks using time-varying traffic demands. Moreover, they effectively model the complex interactions between supply and demand in a transport network. As a result, they capture the spatio-temporal trajectories from origin to destination (OD) of every vehicle and mimic the drivers' route choice behavior (Dynamic User Equilibrium - DUE assumes that no user can improve his/her travel time by unilaterally changing his/her travel path and/or by altering their departure or arrival time) and flow propagation – using a mesoscopic or microscopic traffic simulator. This constitutes a great advantage over traditional models that do not track the movement of individual vehicles but instead split traffic at intersections (Ziliaskopoulos et al, 1996). The DTA model used in this study is VISTA (Ziliaskopoulos et al, 2005) that at convergence reaches a DUE. DTA methods are divided into two groups the analytical and the simulation-based models. The former uses mathematical techniques to solve traffic problems while the latter represents problems as a set of interrelated components that dynamically change based on the main relationships of speed, flow and density.

Alternative simulation methodologies such as CORSIM, VISSIM, PARAMICS, WATSIM do not have a true traveler behavior routing component Peeta and Ziliaskopoulos (2001). They instead move traffic by splitting it probabilistically at every intersection based on historical records or they follow predetermined or DTA paths that are non-DUE. Hence, they cannot be used to accurately predict traffic flow characteristics. A DTA model utilizing a microscopic traffic simulator and reaches a DUE solution is the best model that could be utilized for traffic flow estimation and prediction.

Traditional safety assessment systems employ historical or retrospective analyses instead of prospective. This is because traffic safety analysis requires significant amount of data which in most cases is not available. This as a result limits their effectiveness and accuracy. Moreover, these approaches mainly stem from the engineering discipline and fail to address important dimensions of the problem such as driver behavior. This research aims to address both of these issues by combining influences distilled from the analysis of past accident data with traffic flow data generated from a DTA simulator in a BN. This constitutes an important step forward towards improving safety management practices. The use of a DTA model enhances the limitations of existing practices by providing a consistent way of producing estimates of traffic flow conditions of road networks using limited information from traffic flow detectors. Moreover, it produces timely traffic volume estimates that can be used to assess accident probability.

The paper is organized as follows. Firstly an outline of the method is presented in section 2. Next the core aspects of the method are illustrated along with its theoretical underpinnings. Subsequently DTA and BN techniques are introduced along with the approach followed to implement the VISTA and BN models. The paper concludes with an overview of the tool, the results and a short discussion.

RELATED WORK

Road safety assessment can be performed in different ways; one of the most popular is scenario analysis (Ming-Chih et al 2004), the underlying component of which is the notion of event. An event may be present in a particular accident sequence, and there may be good reason to believe that similar events have caused similar accidents in the past, but that is not sufficient to establish that this event was a cause for the accident at hand. Over the past 15 years or so there has been increased interest in causal inference as a component of artificial intelligence, and one especially useful approach is based on what Pearl (2000) calls a causal model which inherently is the backbone of a BN. Scenarios on the other hand also gained considerable attention in safety engineering as a mean for analyzing accidents. The term 'scenario' is used to designate a prototype or a model of an accident process characterized by chains of facts, actions, causal relations and consequences in terms of damage to people and property. Scenarios are used to design and improve prevention strategies, either by studying past experience or by seeking to foresee chains of situations leading to catastrophes. Therefore, scenario analysis is a causality investigation technique that examines event patterns that can occur either sequentially or in parallel. Scenarios are usually expressed as event sequences that combine information from the environment, the road users, the weather or the road infrastructure. Accident scenarios describe the abnormal sequence of events that can lead to an accident. Erroneous events in scenarios can cascade and therefore dependencies between events need to be considered. In complex systems such as the road networks, where humans and machine agents collaborate, the likelihood of committing an error by either party needs to be investigated. Given this, there are two broad categories of accident analysis, the human related accidents and the machine related accidents. Even though the later can be back-propagated to the designer of the technology these types of failures are treaded independently. Human performance analysis on the other hand investigates various aspects of human information processing in order to indentify environmental or infrastructural improvements to support the limited cognitive capabilities of road users. Therefore, to predict error types and possibilities, it is essential that the scenario analysis incorporates the situational context of the accident. In practice accident forecasting using scenarios is often combined with other forecasting methods, taking into account of possible variability in single scenarios as well as possible relationships between different scenarios. In essence, scenario analysis aims to identify hazardous scenarios and accordingly assign probabilities to them. The outcome of scenario analysis is the identification of causes that lead to an accident. However, the two main problems in scenario-based approaches are the lack of reliable techniques to automate the generation of sufficient set of scenarios to assess safety and the lack of data to generate accident models. For the first problem, several approaches have been proposed that ended up with too many scenarios that drawn the safety assessment process in excessive detail. The latter problem constitutes the second big bottleneck and is partially addressed in this study. Four techniques have been used for scenario accident analysis, namely, Bayesian Networks, Fault Trees, Petri nets and Event trees. Bayesian networks are probabilistic graphs that model scenarios in causal networks. Fault and Event trees, are logic block diagrams that model a system in terms of the states or events that its components can take. A Petri net is a formal, graphical network used for describing discrete dynamic systems. Event trees clearly present the agents involved in the system while Fault trees the events that affect them. Our scenario representation and assessment approach is based on the BN paradigm, where BN constitute probabilistic graphical models that enable reasoning under uncertainty.

The design of scenarios however requires dynamic and static contextual information to describe the traffic conditions and the infrastructure. However, in most of the times these data is unavailable or very limited since sensor-based traffic data collection is pathological to coverage, cost and real-time issues. One of the main contributions of this work is the use of a simulation-based Dynamic User Equilibrium (DUE) DTA traffic simulator to produce estimates of traffic flow characteristics – mainly traffic flow and speed - in 15-minute time intervals. These estimates are then used to normalize the accident records based on a roadway section, link, movement or location basis – under this implementation the roadway network was aggregated into links only.

Related accident prediction approaches such as the one employed by Simoncic (2004) utilize probabilistic modeling through BNs. Their work illustrates the application of BN to model road accidents and accordingly make inferences for accident analysis. The main limitation of this work is that it concentrates solidly on the development of the BN without providing any substantial evidence of its performance. Work by Hu et al. (Hu et al, 2004) also uses a probabilistic approach to predicting road accidents through intelligent surveillance of vehicle kinematics; however, their method does not address the causal aspects that lead to observed behaviors and hence cannot be easily generalized. State-of-the-art tools in accident prediction, such as SafeNET 2 (Software for Accident Frequency Estimation for Networks), use traffic flows and geometric information to assess accident risk (TRL, 2007). However, SafeNET 2 does not address the dynamic aspects of road networks using simulation. Hence, their traffic flow estimates are generic which in effect could lead to inaccurate conclusions.

METHODOLOGY

The road safety analysis method presented herein is based on the integration of DTA-based VISTA simulator (Ziliaskopoulos and Barrett, 2005) with BN technology. The use of a traffic simulator is employed for the following two reasons. Firstly to estimate the traffic flow conditions under which a set of accidents occurred at a homogeneous roadway section or location for a 15-minute time interval of the day. This information in accordance with accident historical data formed the basis to develop the BN model. The time interval of the day (weekday, Saturday, Sunday, special day, season, other) should be defined based on a statistical analysis of the traffic flow conditions initially in 15-minute time intervals and subsequently in larger categories throughout the day). This methodology will aid in the normalization of the accident rates that occur at a specific roadway section, location or movement under similar traffic conditions. The second reason is prediction of future traffic conditions and the new infrastructure changes, based on which the BN will be employed to produce estimates of accident risk per homogenous roadway section, link, movement or location. The existence of this combined BN-traffic simulator will then allow transport agencies to design the transport network either in the short or long term in such a way to reduce the occurrence of accidents.

The proposed method can be generalized by a number of steps:

- Implement a simulation-based traffic simulator to predict the 15-minute traffic flow characteristics per roadway section, link, movement or location. Estimate the corresponding accident rate based on the estimated 15-minute traffic flow rate.
- Compile and integrate the infrastructural and traffic control properties into the BN.
- The above two steps produce the static and dynamic elements of each roadway section, link, movement - infrastructure, traffic control and estimated 15-minute traffic flow characteristics.
- Specify the minimum acceptable level of safety for the design under investigation.
- Accident risk estimation. Start the integrated BN simulation process to assess the accident risk per roadway section, link, movement or location. The integration of VISTA with the BN is done using a developed Java software. BN input in combination with prior BN knowledge is used to assess accident risk. Dynamic input to the BN is provided by the DTA simulation on a step by step basis.

a. For the development of the BN topology and the parameterization of its prior knowledge, historical road accident data and VISTA-generated traffic data were used.

DEVELOPING THE VISTA MODEL

An important contributing factor to accidents occurrence is the traffic flow characteristics of the roadway section, link, movement or location. Therefore, it is essential to predict the traffic conditions of each road section at different time intervals of the day. VISTA is a powerful DTA simulator that enables the prediction of traffic conditions using prior data of driver dynamics and road network's infrastructure. The main components of the VISTA DTA model are:

1. The 15-minute dynamic OD matrix. This was estimated through the use of a static OD matrix developed by the Cyprus Public Works Department (CYPWD) and historical traffic counts collected in 2009.
2. Geographic Information System **(**GIS) and roadway geometry. The GIS was provided by the Cyprus Lands and Surveys Department (CYLSD). The roadway geometry was compiled from CYPWD records and manual surveys by CTL Cyprus Transport Logistics Ltd, Nicosia, Cyprus via Google Earth and on site inspections.
3. Traffic control data. Signal timing for 148 intersections, yield and stop control, speed limit and turn restrictions were provided by CYPWD.
4. Bus data. Bus routes (28), schedules and bus stop locations were provided by CYPWD.
5. Traveler information data. None available
6. Traffic flow characteristics data. Historical traffic counts and travel time studies were provided by CYPWD.

The developed VISTA model features a total of 517,514 OD trips that correspond to 622 OD pairs of passenger cars, 148 signalized intersections, and a set of 28 bus routes.

TRAFFIC FLOW PARAMETERS FOR ACCIDENT ANALYSIS

Road accident are influenced by a large set of parameters some manifested same latent. Manifested parameters include, traffic and weather conditions, and vehicle and infrastructural properties. Latent parameters include aspects relating to human perception, decision making, cognition and psychology. The following list depicts manifested conditions under which accident could occur:

Traffic flow rate (vehicles/unit of time, vehs/hour): Number of vehicles per unit of time at the time of accident occurrence. This parameter is known only in locations and roadway sections where traffic count sensors exist and are recorded at the time of occurrence. A surrogate measure is the estimated traffic flow rate through the implementation of a traffic simulator – in this application we utilized the VISTA DTA model to produce 15-minute traffic volumes.

The vehicle speed (mi/hour or Km/hour): the speed of the vehicles involved in the accident. This parameter is reported (not always) in the police report.

The distribution of the speed (mi/hour): the distribution of the speed during the 15-minute time interval that the accident occurred during the day. This parameter can be estimated from traffic flow detectors at some locations or they can be estimated through a traffic simulator. In this study the distribution of the speed during a 15-minute time interval was estimated through the VISTA DTA model.

Acceleration or deceleration (mi/s^2 or Km/s^2): The acceleration or deceleration of the vehicle(s) involved at the accident. This parameter was not utilized in this study yet it is a very important one in the characterization of the conditions under which an accident occurs. This parameter maybe estimated through Video Image Processing (VIP) where video cameras are installed for such purpose. The best methodology in determining the acceleration/deceleration is through GPS enabled devices. As more vehicles and/or drivers are equipped with GPS-enabled devices such as cell phones or in-vehicle devices then it will become easier to produce estimates of the vehicles' speed/travel time, acceleration and deceleration. A calibrated microscopic traffic simulator maybe utilized to estimate the distribution of the acceleration/deceleration for a specific time interval of the day. The implementation of calibrated microscopic traffic simulators throughout a transportation network is strongly recommended to produce estimates of the state of the system throughout the day in combination with DTA models - whereas the DTA produces the paths and the micro-simulator the traffic flow propagation.

Gap acceptance (time headway (s)): the gap available at an adjoining lane during the occurrence of an accident. This parameter is rarely known unless a VIP sensor is in place. Where such a sensor is present then the distribution of the gaps that are used by travellers may be estimated. These distributions throughout the network could then be used to calibrate a microscopic traffic simulator. As mentioned we did not utilized a microscopic traffic simulator for this study.

Car following headway (s): the car following headway during a rear-end accident. This parameter is usually estimated from police reports through the use of the skid marks on the pavements (if such marks are available). However the proliferation of the use of antilock braking systems makes this methodology questionable as many drivers do not know how to use them properly and the police report may not offer such information (whether an ABS is in place). A calibrated traffic simulator may be utilized to produce a distribution of the car following headways. This parameter was not utilized in this study.

Traffic control parameters: the traffic control parameters (e.g. signal timing) at the time of the accident is rarely known or reported. The model used in this study utilized the average traffic signal timing parameters. A calibrated microscopic traffic simulator models the traffic flow parameters in greater detail and produces more robust results. The BN takes into consideration whether we have signalized or non-signalized intersections including the speed limit.

Traveller information devices (such as Dynamic Message Signs): no such devices existed in Nicosia, Cyprus until the end of 2009.

Environmental, weather and pavement conditions: These are included in the police report and are taken into account via the BN.

Driver type: The police records include various characteristics of the drivers involved in an accident such as age and gender. The driving behavior (aggressiveness is not reported). The driver aggressiveness can be estimated through studies of the transport network, which can then be used to calibrate a microscopic traffic simulator.

NORMALISATION OF ACCIDENT RECORDS

The normalization of the accident records is of principal importance to traffic safety analysis. The accident rate is defined as the number of accidents occurred at a roadway section or location per Million Vehicles Miles (MVM) travelled. Traditionally, this parameter is estimated using the Annual Average Daily Traffic (AADT). This however, constitutes a crude estimate and provides limited accuracy. In this study, the accident rate is defined as:

Accident Rate (AR) = Number of accidents reported/estimated traffic flow rate per time period of the day

The AR for all accidents occurred is estimated through the use of the VISTA DTA model that was calibrated for a typical weekday of the year. This parameter needs to be estimated for each season - to account for fluctuations in demand - of the year based on the local traffic conditions. This would then yield to a set of DTA models for each statistically different "traffic" season. Similarly, a different DTA-traffic simulation model could be determined for Saturdays and Sundays and any special days that have statistically different traffic patterns throughout the 24-hour time period.

Given that the traffic flow rate fluctuates throughout the 24-hour time period, an analysis was conducted to divide the time period of the day into distinct traffic flow periods that have common traffic flow characteristics (volume and speed). The estimated VISTA DTA 15-minute traffic flow rates for links 6, 9, 12, 17 are depicted in Figure 1 for a typical 24-weekday. Figure 1 demonstrates that different links peak at different time periods of the day. Given the different working hour daily patterns for the government, bank and semi-governmental organizations it is recommended that a different DTA and/or micro-simulation model is developed. For example, banks work a full day on Monday's (8:00 – 18:00) and government employees work a full day on Wednesdays (7:30 – 18:00) with a one-hour break at noon time. A typical workday for government employees is from 7:30 to 14:30 with no break in between. As such it is best to develop a different simulation model for each day of the week. Further different models need to be developed for the various seasons and holidays as the traffic patterns change substantially. It is noted that these models will need to be continuously calibrated in order to produce accurate estimates of the traffic flow rate.

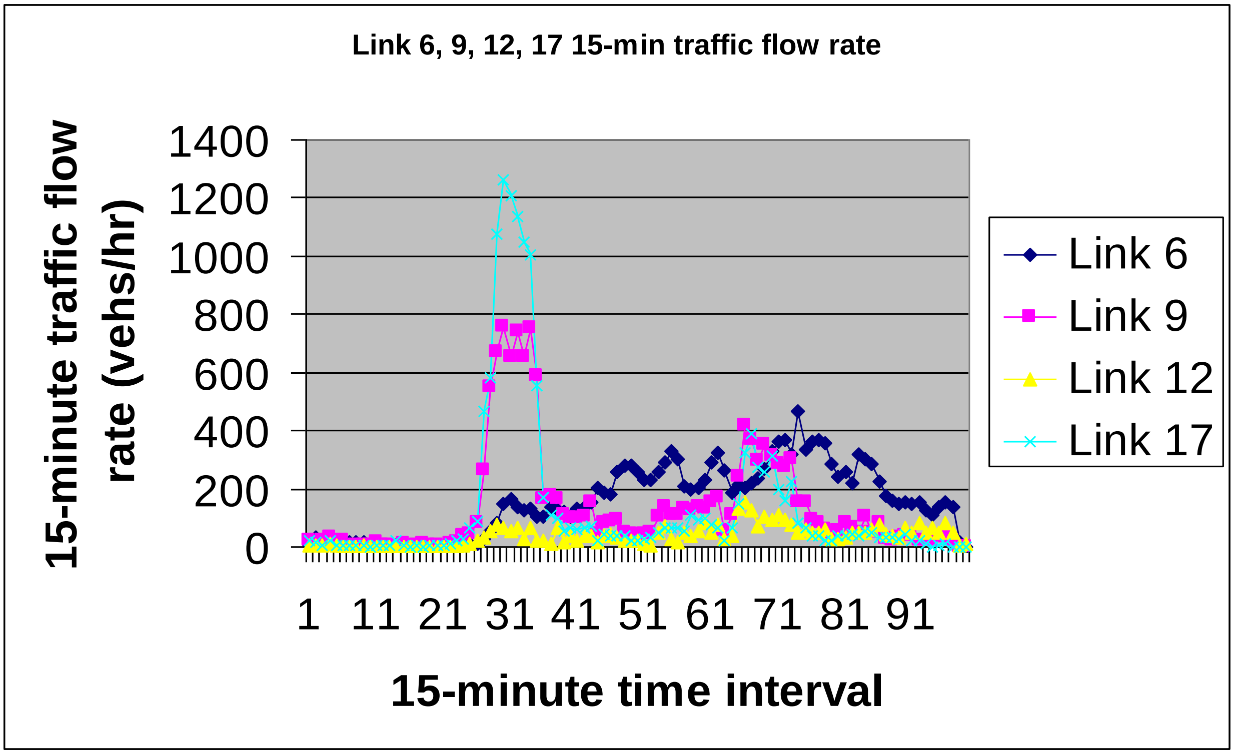

Figure 1 Traffic flow rate (vehs/hr) for link 6, 9, 12, 17 vs. 15-min. time interval

BAYESIAN NETWORKS

BNs are directed acyclic graphs of causal influences, where the nodes represent random variables, and the arcs represent (usually causal) relationships between variables. The two main components of BN are the causal network model (topology) and the conditional probability tables (CPT). The model causal relationships are expressed as directed acyclic graphs. Variables are denoted by nodes in the model and can have any number of states, so the choice of measurement scale is left to the analyst's discretion. Causal relationships among variables are described by arcs among nodes. CPTs describe the prior knowledge of the problem domain and explicitly specify the causal dependencies in terms of conditional probability distributions. Parameterizing the CPTs is often the most demanding task in BN development, as the number of probabilities can be counted in hundreds or even thousands. CPTs can be inferred from data when available or subjectively specified by experts. The former is more objective, however it is unlikely to have all the data needed to specify all CPTs in a model, hence the use of experts is sometimes imperative. BNs can be used in two main types or reasoning bottom-up/diagnostic and top-down/predictive. The former infers the most likely cause given evidence of an effect. While the latter, "top down", deduces the probability that a certain cause would have given a specific effect.

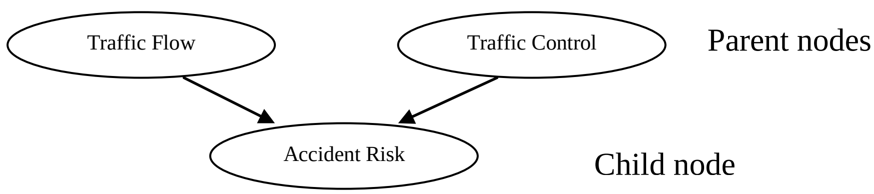

Figure 2 Example BN topology of Accident Risk

Formally, a BN encodes the joint probability distribution over a set of n variables X = $\{X_1,\ldots,X_n\}$. Therefore, let us denote by X_i a random variable, and by Π_i the set of parent nodes of X_i. Then the joint distribution of X can be expressed as the product of the conditional distributions of each variable given its parents, where **x** represents an instantiation of **X**, $\boldsymbol{\pi}_i$ an instantiation of Π_i, and x_i denotes the state of $X_{i,}$:

$$p(X) = \prod_{i=1}^{n} p(x_i|\boldsymbol{\pi}_i) \quad (1)$$

The conditional probabilities described by equation (1) are presented in the CPT. When the topology and CPTs have been completed, Bayes' theorem can be used to diagnose a cause given an effect or the chain rule (1) to predict an effect given a number of causes. The theorem is shown in equation (2):

$$p(x_i / x_j) = \frac{p(x_j / x_i)\, p(x_i)}{p(x_j)} \quad (2)$$

where,

$p(x_i/x_j)$ = posterior (unknown) probability of x_i given x_j
$p(x_j/x_i)$ = prediction term for x_j given x_i
$p(x_i)$ = prior (input) probability of x_i

$p(x_j)$ = input probability of x_j

or, less formally:

$$\text{Posterior\_Probability} = \frac{\text{Likelihood} \cdot \text{Prior\_Probability}}{\text{Evidence}} \tag{3}$$

The example in Figure 2 shows two influences on accident risk (AR), namely, traffic flow (TF) and traffic control (TC). Let us denote by W the AR, M the TF, and S the TC. Their corresponding states are described by w, m and s respectively. The variables can have any number of states, so the choice of measurement scale is left to the analyst's discretion. Let us denote by n_W, n_M and n_S the number of states for W, M and S respectively. In the following sections, we assume that the variables can take three discrete states ($n_W = n_M = n_S = 3$), namely, high (h), medium (m), and low (l). Therefore, based on the above example, to diagnose (bottom-up) the probability that traffic flow is m_j given that we have evidence that accident risk is s_k, we use the Bayes' rule:

$$p(m_j|s_k) = \frac{p(s_k|m_j)p(m_j)}{p(s_k)} \tag{4}$$

In predictive reasoning the chain rule is applied, to calculate the likelihood that accident risk is w_k , given evidence of traffic flow is m_j and traffic control is s_i,:

$$p(s_i, w_k, m_j) = p(s_i)p(w_k|s_i, m_j)p(m_j) \tag{5}$$

Input evidence values are propagated through the network, updating values of other nodes as explained above. The network predicts the probability of certain variable(s) being in particular state(s), given the combination(s) of evidence entered. BN models are extremely computation-intensive when the topology and the variable states increase. However, recent propagation algorithms exploit graphical models' topological properties to reduce computational complexity (Pearl, 1988, 2009). These are used in several commercial inference engines such as HUGIN (Kjaerulff, 2008). BNs have to conform to a strict hierarchy since cycles lead to recursive and non terminating propagation of probabilities by the algorithm. This imposes some compromises in modeling influences, which can be partially overcome by introducing additional input nodes to model cyclic influences, although this increases complexity of the network and the control process for the algorithm.

MODELLING ACCIDENT RISK IN BN

For the development of the accident risk BN it was imperative to firstly identify the variables and their state, find dependencies among variables and finally encode the prior knowledge the express the causal influence that variables have between then in the CPTs. Development of the BN model was based on machine learning using accident data obtained from the Cyprus Police. However, due to the limited scope of the data, important information that significantly affects accident risk such as traffic flow and road infrastructure was missing. Hence, to enrich the initial dataset with this missing information we used the VISTA simulator to generate traffic flow data for each accident record. In addition, due to limited information regarding infrastructural properties in the accident reports, it was necessary to map each accident on a geospatial GIS platform and subsequently import these on VISTA (Figure 3) to obtain more information regarding the infrastructure at each accident point. Once this mapping was achieved additional information regarding the road network at the accident scene was obtained from VISTA. This helped to define the causal relationships of the BN variables that described the infrastructure and the traffic dynamics. Parts of the accident dataset were used to train the BN and others to identify black spots on the network. These points were later used to validate the BN model.

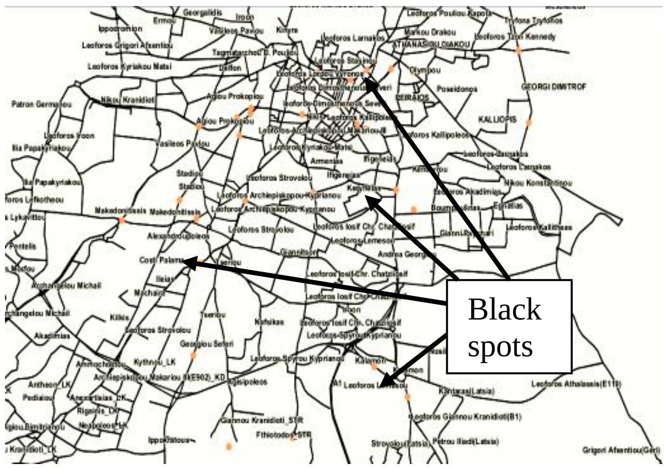

Figure 3 Road network black spots as overlaid dots in VISTA Java GIS

Preliminary compilation of the initial Police dataset was performed with the SPSS statistical package. The accident dataset covered all accidents occurred in the Nicosia area from 2002 until 2008 and comprised over 9000 records. Each record consisted of 43 (six continuous and 37 categorical) input parameters covering global, local, temporal, accident, driver and car characteristics collected at the site of the accident by the police officers, eye witnesses and the involved parties. Each record was associated with a single categorical output parameter pertaining to accident severity, namely light, severe and fatal, as evaluated by the police officer at the site of the accident.

Dataset pre-processing involved two steps (a) replacement of missing and erroneous (e.g. falling outside the acceptable range) parameter values by the mean value of the parameter values of the other (assumed correct) records, and (b) grouping neighboring or related values of multi-valued (i.e. containing more than 12 values) categorical parameters so as to have a manageable number of intelligible as well as regular categories per parameter.

Statistical analysis relating the 43 input parameters (independent variables) to accident type (dependent variable) reveals that the Spearman correlation coefficient values between the inputs and the output are low (Figure 4), while the Spearman p-values are relatively high. Owing to the sufficient size of the database however, it is still possible for some of the correlations to be statistically significant. In support of that, accident type prediction was found far from satisfactory when only the statistically significant/correlated parameters were employed, thus demonstrating that statistically derived feature selection cannot be performed on a statistical basis for extracting the input parameters that affect the output and discarding those that do not provide accident type-related information.

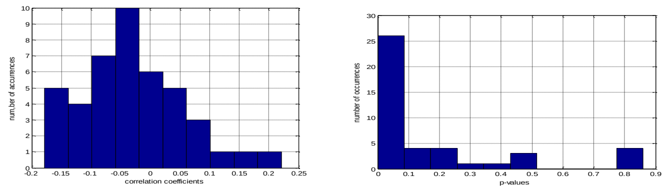

Figure 4 Statistically derived correlation coefficients (left) and p-values (right) between the 43 input parameters and accident type.

The processed accident data was subsequently used to identify the core variables of the BN model. To reduce the complexity of the process and the model itself, the dimensionality of the initial data set was reduced using Principal Component Analysis (PCA). In principle, PCA projects the original data into a new set of orthogonal axes in such a way that the original multidimensional dataset with possibly correlated parameters is linearly transformed into a novel dataset of identical dimensions but with totally uncorrelated parameters. Owing to the fact that each new axis is selected so as to maximally expose the (remaining) variability of the dataset, it is not unusual for the first few axes of the PCA mapping to account for most of its variability. Hence, small PCA axes are generally sufficient in representing the original data with minimal loss of information. Results from this process yielded 12 artificial variables.

Additional information from the accident location was obtained from VISTA using the geospatial coordinates. Finally the traffic volumes along with traffic speed of vehicles were mapped to each accident record given the time of the accident the geospatial coordinates. These were used to calculate traffic density for each accident location. Merging of the results from the dimensionality reduction using PCA and the traffic density and infrastructural properties from VISTA produced 19 variables that were the baseline for learning the BN topology (Figure 5) and the CPT. The machine learning algorithm used to develop the BN model is expectation maximization (EM). EM is a robust algorithm that enables learning of BN model parameters from incomplete data. In essence, EM algorithm is a method for finding the maximum likelihood, based on unobserved latent variables. EM is an iterative method which alternates between performing an expectation (E) and maximization (M) step. In the E step, we calculate an expected value of the log likelihood based on an estimation of the unobserved data, while in the M step, we find the parameter that can maximize the log likelihood. The EM steps improve the log likelihood while iterating and achieve an optimal when it converges. The EM algorithm is part of the HUGIN tool that we used to develop the BN model.

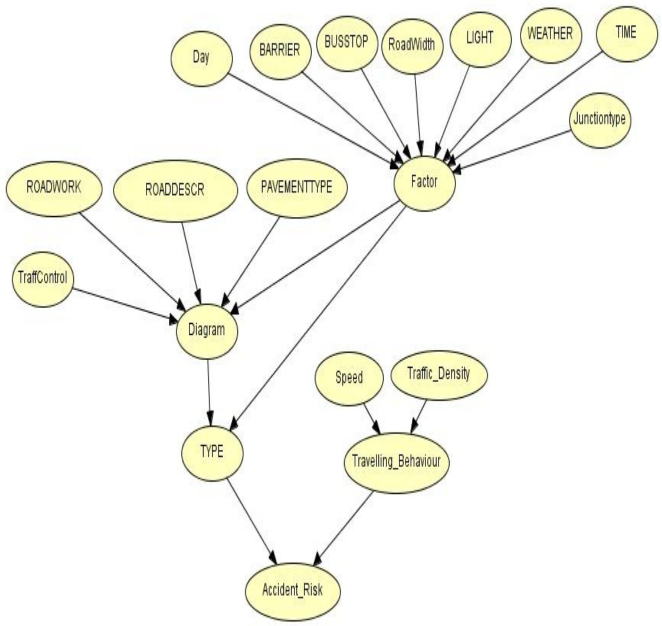

Figure 5 Data generated BN topology

BN MODEL VALIDATION

To estimate the accuracy of the developed BN model, five-fold cross validation was performed. Accident database that was enhanced with traffic data was randomly partitioned into five folds of equal number of records. Subsequently, and for each fold, four of the sets were employed for training the model while the remaining set was reserved for testing. Prediction accuracy was calculated by the weighted average of the test results of the five folds. Overall, the results of the validation process demonstrated that the model can accurately predict accident risks. However, the fact that traffic volume is based on simulated results biases the outcome. Therefore, an additional validation study needs to be performed to verify that the model performs well in realistic settings.

An additional validation study sought to evaluate the effect of certain input variables to the target variable, namely, accident risk. Therefore, attribute relevance analysis (Figure 6) was performed using the Envisioner data mining tool to compute the relevance between each causal factor to accident risk. The relevance of variables to accident risk was compared against the learned conditional probability that emerged from EM algorithm and the posterior probabilities computed by the BN with the independent instantiation of each leaf node variable. The results highlighted a high correlation between the relevance of certain variables to the target variable and the causal effect of the same variables to the target variable.

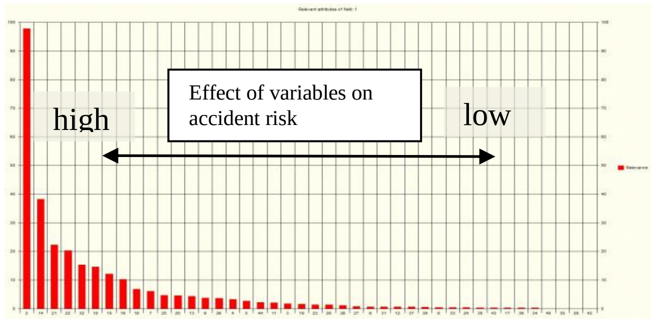

Figure 6 Relevance Analysis results

THE ROAD SAFETY ASSESSMENT TOOL

The assessment of road safety is achieved through the combination of the VISTA and BN technologies. The main components of the tool's architecture are: the BN engine, the accident risk assessor, the VISTA simulator, the data pre-processor that incorporates the scenario generator, the results analyzer and the visualizer. Figure 7 depicts these along with the subcomponents of the VISTA technology.

The system was developed using a component-based software engineering methodology. With the initial specification of the system requirements captured, we proceeded in the identification of suitable software components that matched the initial system requirements. These components were subsequently integrated to implement parts of the system's functionality. In particular the Bayesian inference engine and the visualization components were selected after thorough investigation. The glue-code that enabled components integration was implemented in Java. The risk assessor quantifies accident risk using a Bayesian inference engine that utilises the probabilistic model of accident risks. Input to the BN assessor is categorized into static and dynamic. The former is obtained from the VISTA database and the latter is the output of the VISTA simulation.

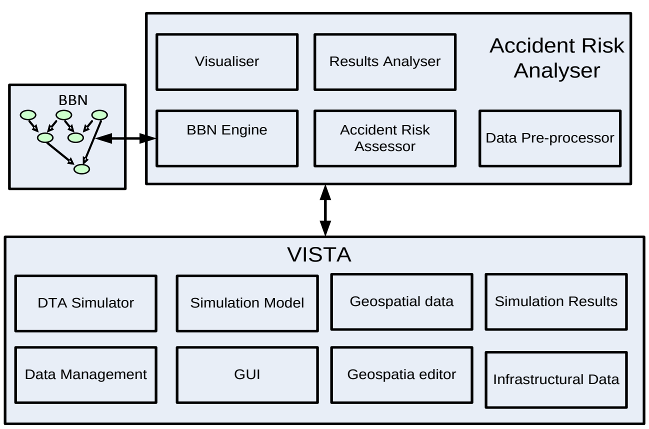

Figure 7 The Software System Architecture

Input to the accident risk assessor is organized in the form of scenarios. An input scenario to the BN assessor is defined by the static and dynamic properties of each road section. Static information is obtained from the VISTA database and in combination with the dynamic input from the simulator provides the baseline for generating a number of plausible test scenarios for each section. Generated scenarios are executed by the risk assessor to quantify the probability of accident. The scenario generator is responsible for generating plausible scenario variations to stress-test the safety performance of the road network. The visualizer processes the results and depicts these to the user graphically. An overview of the tool's information flow is depicted in Figure 8.

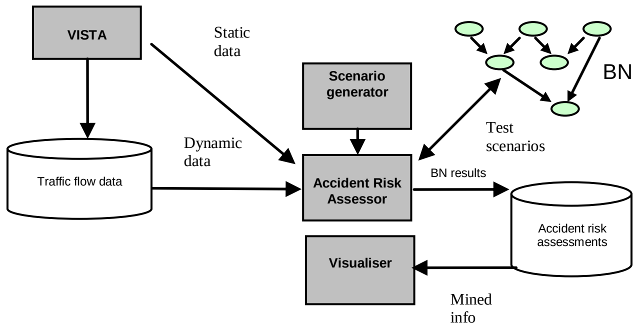

Figure 8 The System components information flow

Scenario input evidence is pre-processed before executed by the BN model, embedded in the risk assessor. Test scenario inputs are propagated down the BN to produce the posterior probability of accident risk per scenario. The integration of the VISTA with the BN model was realized through asynchronous data interchange.

To establish communication between VISTA and the risk assessor it was imperative to pre-process VISTA's output data prior to being utilized by the BN in the risk assessor. Specifically, VISTA variables are continuous by nature, hence, had to be converted into categorical/discrete to be processed by the developed BN that used only discrete nodes. Hence, it was necessary to discretise the output from VISTA prior to instantiating the BN model. For the discretization process it was necessary to refer to domain experts that specified the cut-off values for each variable. Specifically, for traffic volume three states were defined, namely, low, average and high. The first corresponding to less than 100 vehicles per 15 time interval, the second to less than 350 and the last to greater than 350.

RESULTS

Results from the accident risk assessor were used to calculate the accident risk index of each road section. Analyzed scenarios for each segment were labeled accident prone if the estimated BN accident risk probability was above a pre-specified threshold value. BN scenarios that fell below the threshold value were ignored. This enables the safety engineer to alter the granularity of the analysis by altering the threshold value. To produce the accident risk index it was imperative to normalize the number of accidents that were predicted by the BN and where above the threshold value, with the traffic volume per time interval, for each road section. The developed system uses a systematic approach that utilizes the traffic volume estimates from the VISTA simulation and the accidents predicted using the BN risk assessor. Traffic volume acts as a normalizing factor for the number of accidents predicted using the BN risk assessor. This gives rise to the accident risk index for each road section that inherently highlights network's black spots. An illustration of the preliminary results produced by the method is depicted in Figure 9. This figure illustrates a subset of the results and indicates that sections with IDs, 3, 21 and 47 have the highest accident risk index. This enables the safety engineer to introduce appropriate countermeasures to alleviate the problem. These are then implemented in the simulation model. Each countermeasure then undergoes an evaluation procedure in the system to verify that the problem is eliminated prior to being implemented.

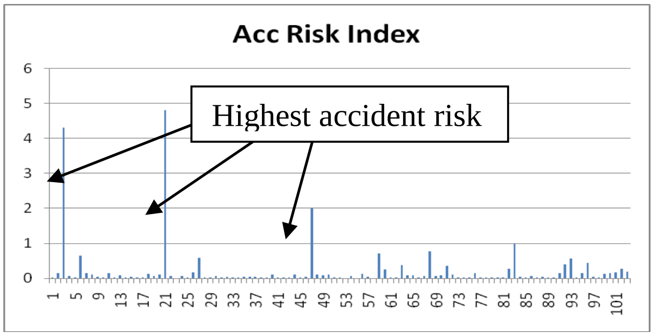

Figure 9 Links on the road network with highest accident risk index

DISCUSSION

The method described herein illustrates a novel approach to quantifying road safety using probabilistic inference with DTA simulation. Integration of VISTA with BN, as presented, enables the combination of static, dynamic, known and uncertain evidence for accident risk quantification. The system combines state of the art technologies in traffic simulation and accident risk assessment. Integration of these provides the decision makers with the necessary means to perform a holistic safety analysis. The method escapes from the problem of traffic data shortage that limits most traditional approaches through the use of DTA simulation. VISTA provides traffic volume data estimates for all road sections, links and movements of the network on a 24 hour basis at the desired time interval – a 15-minute time interval was used in this study. This methodology is implemented as a prototype to demonstrate the methodology rather than an operational model that requires substantial calibration of the underlying DTA model and/or traffic simulator. Once a model is properly calibrated then the traffic flow rate estimates will correspond closely on the actual conditions that the group of crashes that occurred at each roadway segment, link and movement, yielding more accurate crash rate estimates and consequently a better normalizing methodology rather than the AADT.

BNs have been used in road safety analysis to describe and quantify the causal relationships between factors leading to accidents. However, the instantiation of BN with improved assessments of traffic conditions through DTA simulation makes this work novel. BNs gained widespread acceptance with the introduction of computational algorithms that enabled their exploitation. The main limitation of BNs is that they do not provide a direct mechanism for representing temporal dependencies in a problem. Given that many real problems are complex and changeable over time, static BNs are inadequate. Therefore, many improvements have been proposed to deal with this limitation, such as representing probabilities as functions of time or considered each node composing of two parts, i.e. a state value of a random variable and a time interval associated to the change of the state. DBN structure consists of many temporal slices which maintain multiple copies of nodes and connections in a static network and oriented arcs which connect variables in different time-slices. However, such formulations require exogenous knowledge of how the probabilities or states vary over time. Despite that, the benefits of DBN over static are considerable in certain situations. Therefore, considering the possibility that some observations lose their relevance or importance with the passage of time in the simulation, part of our future directions includes the application of DBN paradigm to the accident risk assessment algorithm.

We also note that while the current version of VISTA incorporates a mesoscopic traffic simulator. A mesoscopic traffic simulator does not have the capability to produce the detailed traffic flow conditions under which accidents are occurring. Future research directions include the replacement of the mesoscopic traffic simulator with a microscopic traffic simulator. This will produce estimates of the DUE paths and the associated traffic flow characteristics at the microscopic level (traffic flow rate, speed distribution, acceleration/deceleration speed distributions, gap acceptance distribution, car following headway distribution, other) per time interval of the day. Alternatively, given the slow convergence of DTA models the last iteration of a DTA model could be send to a microscopic traffic simulator to produce the corresponding traffic flow parameters.

Install a traffic flow monitoring system at strategic locations throughout the transportation network to calibrate the DTA-micro model on a daily basis thus reducing the bias of one DTA-micro-simulator representing all daily and seasonal traffic patterns.

Continuously calibrate the DTA-micro simulation model either offline or in real time.

Utilize the calibrated model to produce estimates of the traffic flow conditions based on various infrastructure changes.

Integrate the DTA-micro model with the BN to produce estimates of accident risk based on proposed changes of the transport network.

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REFERENCES

Druzdzel M.J.,van der Gaag L.C. (2000), “Building probabilistic networks: "Where do the numbers come from?" guest editors' introduction. *IEEE Transactions on Knowledge and Data Engineering*, 12(4): 481-486.

Fenton N.,(1999) “Applying Bayesian belief networks to critical systems assessment”. *Critical Systems*, 8, 10 - 13.

FHWA,(2010) "Surrogate Safety Measures From Traffic Simulation Models", *FHWA-rd-03-050 U.S.* Department of Transportation Federal Highway Administration Research, Development, and Technology.

Fleury D., Brenac T., (2001), “Accident prototypical scenarios, a tool for road safety research and diagnostic studies”, *Accident Analysis and Prevention,* 33:267–276

Florian, M. et al.,(2008) "Application of a simulation-based dynamic traffic assignment model", *European Journal of Operational Research*, 189,1381–1392

Hollnagel, E. (1998), *Cognitive Reliability and Error Analysis Method*. Oxford: Elsevier.

Hollnagel, E. D. Woods, and N. Leveson, (2004), *Resilience Engineering and Management*. Aldershot, UK: Ashgate.

Hu, W. X. Xiao, D. Xie et al., (2004),“Traffic accident prediction using 3-D model-based vehicle tracking”, *IEEE Transactions on Vehicular Technology*, 53(3), 677-694.

Kapp, C. (2003),"Who acts on road safety to reverse accident trends", *The Lancet*, 362, 1125-1125.

Kjaerulff, U., Madsen, A., (2008), “Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis”, *Springer*

Lo, H. (1999),"A dynamic traffic assignment formulation that encapsulates the cell transmission model", In A. Ceder (ed.) *Transportation and Traffic Theory*, Pergamon, Oxford.

Ming-Chih Tsai, Chien-Chih Su, (2004), “Scenario analysis of freight vehicle accident risks in Taiwan”, *Accident Analysis and Prevention*, 36:683–690

Pearl J., (2009), “*Causality: Models, Reasoning and Inference*”, Cambridge University Press, 2009.

Pearl J.,(1988), “*Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Information*”, San Francisco: Morgan Kaufmann.

Peeta, S. and Ziliaskopoulos A.K.. (2001). “Foundations of Dynamic Traffic Assignment: The Past, the Present and the Future”, *Networks and Spatial Economics*, 1 (3/4): 233-65.

Simoncic, M. (2004),“A Bayesian Network Model of Two-Car Accidents” Journal of Transportation and Statistics, 7(2,3),13-27.

Sisiopiku, V. and Li X. (2006). “Overview of Dynamic Traffic Assignment Options”, *Proc., 2006 Spring Simulation Multiconference*, Society for Modeling and Simulation International, Huntsville, AL.

Sohn Y., Lee S., (2003), “Data fusion, ensemble and clustering to improve the classification accuracy for the severity of road track accidents in Korea”, Safety Science 41, 1–14

TLR,(2007), “*SafeNET2*”, http://www.trlsoftware.co.uk/news/detail.asp?pid=51&iid=29.

Ziliaskopoulos, A. and Barrett C. (2005), “Visual Interactive System for Transportation Algorithms.” Available online at: http://cluster.vistatransport.com, Accessed Feb. 16, 2006.

Ziliaskopoulos, A. and Lee, S. (1996). “A Cell Transmission Based Assignment-simulation Model for Integrated Freeway/Surface Street Systems”. *Proc., 75th Transportation Research Board*, Annual Meeting, Washington, D.C.