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TOWARDS A USER-CENTRED ROAD SAFETY MANAGEMENT METHOD BASED ON ROAD TRAFFIC SIMULATION

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ABSTRACT

One of the most important gaps in road safety management practises is the lack of mature methods for estimating reliability. Road safety performance assessment systems have been developed; however, these provide only historical or retrospective analyses. Effective safety management requires a prospective viewpoint. The main goal of this research is to assist in reducing accident rates in Cyprus by providing ample time to the authorities to react to high risk situations through a safety prediction early warning system. This ultimately will prevent accidents from occurring which subsequently could save lives. Traditional approaches focuses solidly on empirical data concerning road network dynamic properties, despite the fact that the most vulnerable component of the system is the human element. This paper described the integration of agent-based simulation with Bayesian Belief Networks (BBN) for improved quantification of accident probability. The BBN is developed using multidisciplinary influences.

1 INTRODUCTION

Resent surveys in road traffic accidents in Europe stress the need for improved road safety and traffic management practices. Traffic accidents kill 1.26 million people each year; 2nd leading cause of death among those aged 15–29 (Kapp 2003). The principal component of this research is real time assessment of road safety performance through the development of an early warning system that would enable proactive risk mitigation of road accidents. The literature in road safety performance is categorized into macro and micro level approaches. The former takes a holistic view of the road traffic system where accidents are caused by coordinated events of the system's components which give rise to accident patterns. The latter looks on accidents on an individual component basis and investigates the dynamics of each component's supporting sub-elements. Macro level analyses use statistical techniques to give an aggregated view of historical data and with the use of regression analyses make projections on future system states. These are categorized into four groups: averages from historical accident data, predictions from statistical models based on regression analysis, results of before-after studies, and expert judgments by experienced engineers (USD 2000). Each of these methods however suffers from significant weaknesses. Estimates from historical accident data suffers from high variability. Estimates from statistical models use data of accidents with roadway characteristics (traffic volumes, geometric designs features) in a regression analysis to predict the expected total accidents in particular locations. Regression models on the other hand can lead to unreasonable interpretations of the outcomes. Before-and-after studies have been used for many years to evaluate the effectiveness of highway improvements in reducing accidents. However, most before-and-after studies have design flaws which lead to ambiguous results. Finally, estimate from expert judgment is a feasible method only if the experts have a point of reference due to their inability in making quantitative estimates.

On the micro level, research range from driving behaviour, human performance, man-machine system reliability, vehicle kinematics (USD 2000), (Hu et al 2004) and vehicle ergonomics. Multi-agent systems are adopted as a promising technology for modelling micro level analyses due to their inherent capabilities of dealing with complex interaction among system elements.

The application of deterministic and stochastic techniques in both macro and micro categories varies according to the nature of the analysis. However, stochastic techniques are more favourable for accident prediction due to their ability to model uncertain characteristics of the system. Bayesian belief networks have been applied in complex systems safety analysis as a natural descendant of event trees. Application of the approach in road safety performance prediction is also gaining acceptance. The diverse influences to road safely prerequisite a multidisciplinary approach to its quantification that should address issues such as: Human Factors, Traffic flow dynamics, Driving behaviours and Human Reliability.

No method has been reported to date for real time accident risk prediction using dynamic data sampling from road networks. Most techniques predict accident frequencies based on historical data that give rise to regression analyses (USD 2000). This paper describes a framework based on which information obtained in real time from a road network simulator is combined with human factors theories, and scenario analyses to provide improved accident prediction and safety performance metrics.

Contemporary safety literature (Hollnagel 1998, 1993)(Leveson 1995)(Reason 2000,1990) reached a consensus on the importance of the human element in road safety. Accidents in general occur due to human misjudgement or human error (HE). It has been reported that HE was the sole cause for road accidents in 57% of all cases and was a contributing factor in over 90% (Reason 1990, 2000). Despite these finding no effort has been reported that uses human performance research in predicting road accidents. Complex systems safety assessment techniques use human reliability and human performance theories as the driving forces, together with system resilience assessment through investigation of plausible system pathways that could lead to failure (Hollnagel 2004). Our approach to accident prediction uses these in combination with road network simulation.

Hollnagel (2004) classify accident models in three groups, the sequential, epistemological and systemic. The first describes accidents as sequence of events that occur in a specific order. The second use the metaphor of a disease i.e. the outcome of a combination of factors, some manifested, some latent. Classical example is the swish cheese model of Reason (1990,2000). Finally, systemic models describe performance at the level of a system as a whole (Systems Theory). The proposed approach is based on both sequential and epistemological principles. Our previous work on complex socio-technical system reliability analysis (Gregoriades et al 2005, 2007) (Sutcliffe 2007) and workload prediction (2005) produced a method and a tool for assessing the reliability of such systems based on Bayesian Belief Networks (BBN) and scenario based testing technique. The method exhaustively tested the reliability of these systems based on a number of high level scenarios. This approach analyses a limited combination of system components properties due to computational constraints. This paper is a continuation of this work and addresses the accident prediction problem by increasing the scope of the scenario analysis technique through automated scenario generation and the introduction of agent-based simulation. The underlying risk quantification mechanism is based on Bayesian inference. Real time monitoring of traffic data is achieved using a software bridge that enables the communication between the BBN inference engine and the road network simulator. Plausible scenario variations are generated using existing evidence and contextual knowledge representations of most likely event that can occur.

This research views road networks as complex systems composed of vehicles, drivers, road geometric designs and intelligent technologies in the vehicle or in the road design (intelligent highways). Assessing safety in such systems is a complex problem that requires a multidisciplinary approach. This paper describes a novel method for road safety quantification and prediction using diverse input from Human Factors, Agent-based Simulation, Uncertain reasoning, Knowledge Engineering and Systems Engineering domains. The research method described is based on an experimental design of an early warning system to give traffic controller ample time to react to situations with high accident risks. The research question we aim to answer is whether the proposed method provide a good predictor of road safety. This paper describes the current state of our research and concentrates on the development of the road accident prediction model using BBN.

The paper is organized as follows: firstly the main components of the method are illustrated. Subsequently, the underlying BBN technology is explained and the BBN model for road accident quantification is described. The paper concludes with a brief discussion.

2 THE METHOD

The principal components of the method are: (1) a BBN model for accident risk quantification using real time observations from the road network simulation (2) a microscopic simulation model of the road network under study (2) a multi-agent model with contextual awareness capabilities that provides information regarding the state of the road network in real time to the BBN risk assessor (3) an automated scenario generation mechanism based on Monte Carlo sampling and contextual information models, described by knowledge representations (Ontologies) of accident scenarios. Generated scenarios aim to stress-test the reliability of current or prospective road network designs by varying the scenario conditions according to the most likely deviations from the observed states of emerging scenarios as they are executed on the simulator.

The method is split into two phases, (A) the development of the microscopic simulation model and the BBN accident assessor phase and (B) the development of the agent-based monitoring system phase. During Phase A, we developed a preliminary micro-simulation model of a road network in Cyprus using statistical data of traffic volumes from the Department of Public Works. An important aspect of this problem is the modelling of the driving behaviours. This is achieved using the Rumar's model of information processing that describe driver's perception, decision making and action-taking processes. Road-users are modelled using Rumar's driving behaviour model, and the situations that emerge from these are largely dependent on individual behaviour and interactions between road-users. Driver behaviour models allow us to introduce behaviour caused by imperfect perception, decision-making and action. Bad judgment and not anticipating other road-users actions, are errors that can be introduced into the simulation. An agent model of the driver, based on Rumar's model of information processing, allows a computational framework that is comparable with capabilities that are used in advanced game research where the modelling of perception, cognition and communication of individual agents is present. Therefore, driver behaviours that corresponds to: car following, lane changing, gap acceptance and obstacle detection, are executed in the microscopic simulation based on information perceived, analysed and actions performed by the driver. The former describes the driver's acceleration and deceleration patterns i.e. a conservative driver maintains the speed of the leading vehicle while an aggressive driver tries to attain its desired speed. The latter theory describes the behaviour of drivers when changing lanes or the gab between two vehicles. Driving behaviours were obtained from past ethnographic studies and past research. Preliminary results were embedded in the road network's micro simulation.

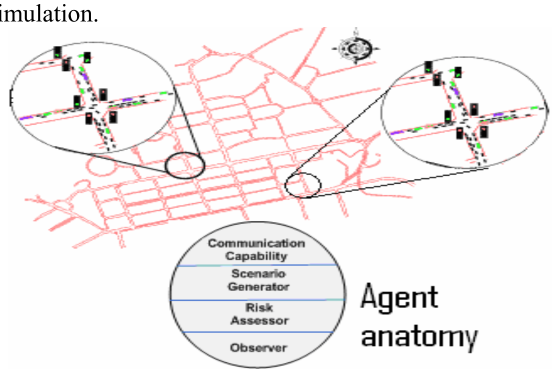

Figure 1: Road network micro simulation and agent based monitoring components

For the accident risk quantification part, we conducted an extensive literature review in safety engineering, accident causation, traffic and human factors theories to identify the main influences to road accidents. Additionally, we collected and analyzed empirical data from the Police, the Ministry of Transport, Communications and Public Works department (PWD) of Cyprus to identify accidents causations and driving behaviours. Based on these we created a taxonomy of influencing factors and subsequently a topology of the BBN model for accident prediction. Historical data of accident causes and conditions, acquired from the police have been also used to generate parts of the Conditional Probability Tables (CPT) of the BBN model.

Phase B of our method addresses the development of an agent-based monitoring system to track changes in traffic volumes, densities, behaviours and speeds from the simulated road network. Fused observations from the simulation will be used as input to the BBN risk assessor to quantify accident likelihoods. Our approach aims to stress test road networks by generating plausible scenario variations based on observed initial conditions (evidence) and network characteristics obtained from an ontological representation of the domain. Application of knowledge engineering technologies such as ontologies are investigated in accordance with Mote Carlo sampling techniques in an attempt to generate adequate plausible scenario variations, while overcoming the combinatorial explosion problem when generating scenarios using exhaustive pairwise combinations of all possible input events. Each software agent is embedded with an accident risk assessor, a scenario generator and an observer as depicted in Figure 1.

The justification for requiring microscopic traffic simulation is based on the need to model the dynamic interaction patterns of the humans, vehicles and the environment under which they operate. However, these are complex processes that require a micro rather than a macro approach in order to emulate realistically a road network. Micro-simulation tools analyse traffic phenomena through explicit and detailed representation of the behaviour of individual drivers and the environment in which they reside, to realistically mimic real world traffic situations. They are ideal tools to analyse and experiment with different road designs and control strategies under constrained environments. Each entity in the system is modelled according to its inherent behaviours. Therefore, vehicles, traffic lights and road designs are represented by entities in the simulator that interact to unfold the dynamic behaviour of the system. The purpose of the simulator is twofold: firstly to generate simulation results based on which the conditional probability tables of the BBN model will be generated. Secondly, to mimic the behaviour of a road network and its dynamics based on which observations can be made and accordingly assess the risk of accident occurring in a real time fashion. Currently, the basis for every intelligent system that helps to alleviate road accidents is information about the current traffic situation. Typically, traffic data is collected by locally fixed detectors in the road network. However, a lot of road networks in Cyprus are not equipped with detection devices to gather information concerning traffic volumes and speeds. Therefore, we used a simulator that realistically mimics the dynamics of an existing road network after being calibrated using data from manual observations performed by the PWD. Software agents collect traffic data in real time for each road section. The risk assessor calculates the accidents posterior probability using Bayesian inference, based on input evidence provided by each agent's observer. The scenario generator supplies the risk assessor with a number of plausible scenario variations, to stress test the safety performance of each road section. Agents communicate via their inherent communication capabilities and accordingly inform the controller software agent of the overall safety performance of their road section.

The road network simulation model will be configured further based on identified driving behaviours. These will be obtained from human factors and cognitive theories (Hollagel 2000)(Rumar 1985), past ethnographic studies, traffic theories (USD 2000) (car following, lane changing) as well as field data obtained from the police and past research projects such as the SARTRE (Cauzard

1993). We aim to augment traditional models of driving behaviours with results from the above to improve the accuracy of the simulation. Current models of driving behaviour in microscopic simulators are limited to traffic theories described by the "car following" and "lane changing" models. In this study we aim to introduce psychological properties that can affect driving behaviours such as sensation-seeking, anxiety and mood, similarly to (Oltedal 2006)

3 SCENARIO MODELLING

An important element of our approach is the notion of scenarios that describe the situations that can emerge in the road network. During scenario-based testing a number of scenarios are used to stress test the safety performance of a current or prospective road system. Scenarios have gained widespread attention for validating the design of complex socio-technical systems (Gregoriades 2004). By road system we define the socio-technical system composed of machines (vehicles, GPS etc), humans, the tasks that they undertake (driving, cycling etc) and the environment under which they operate (road designs, weather etc). Scenarios are described as combinations of events that can occur simultaneously using properties of each of the above system components. Each component is characterised by a number of parameters. For instance the environment is described by the weather, temperature, humidity and visibility. The driver component constitutes the most diverge element of the system due to its high unpredictability. A high percentage of accidents would not occur if humans did not commit to errors of some kind. However, humans are influenced by variety of factors that would be "overkill" and too cumbersome to argue that we can model them all in scenarios. Our approach addresses these issues by modelling the main properties of the human element that can cause accidents, based on human Factors and Human Reliability theories (Bailey 1996)(Williams 1988)(Rouse 1993)(Wickens 2002). Since scenarios constitute the underlying concept of our analysis, it is imperative to provide a technique to automate their generation. The objective is to generate a sufficient number of scenarios to provide a thorough test of the safety performance of the system. However, a problem of past attempts to scenario generation emphasised the problem of producing too many scenario variations that caused overloading during their analysis. To overcome this problem our scenario generation method will generate plausible scenario variations using an ontology that characterise the domain. A Monte Carlo sampling technique will be used to sample the most likely events that can occur from the ontology given certain evidence from the simulation. The concept is analogous to Broadhurst's (2005) techniques for road safety assessment where the likelihood of all possible future scenarios in a multi-object road scene is assessed based on the risk likelihood of each possible future trajectories of each moving object such as vehicles and pedestrians. Our method differs from Broadhurst at the level of abstraction.

4 PROBABILISTIC ASSESSMENT USING BBN

In order to improve the fidelity of our approach and escape from the deterministic assessment of road accidents risks we needed to consider and model the uncertainties involved among the road accident influencing factors. There are a number of candidate approaches for modelling uncertainty that can be used, such as Bayesian probability, Dempster-Shafer theory, Fuzzy sets or Possibility theory. Bayesian probability theory is the most mature methodology which employs qualitative and quantitative modelling constructs to represent a problem. Bayesian probability provides a decision theory of how to act on the world in an optimal fashion under circumstances of uncertainty. It also offers a language and calculus for reasoning about the beliefs that can be reasonably held, in the presence of uncertainty, about future events, on the basis of available evidence (Pearn 1988). BBNs are useful for inferring the probabilities of future events, on the basis of observations or other evidence that may have a causal relationship to the event in question. BBNs strength resides in their ability to reason under incomplete and uncertain information. The two main components of BBN are the topology and the conditional probability tables (CPT). The topology corresponds to the qualitative part of the model where the various dependencies of the variables that characterised the domain are explicitly defined. These relationships are expresses as directed acyclic graphs. The CPT which corresponds to the quantitative part describes the prior knowledge between the various causal dependencies in terms of conditional distributions. Bayesian Networks 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.

The BBN model of Figure. 2 shows two influences on road accidents: driving behaviour and road design. Variables can have any number of states in a BBN, so the choice of measurement scale is left to the analyst's discretion. For the illustration we have assigned these variables to one of the two possible states: *Good*, or *Bad*.

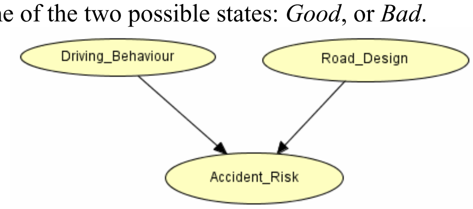

Figure. 2. Part of the proposed BBN model with two parents and one child.

BBNs provide an efficient factorisation of the join probability distribution (JPD) over a set of variables with defined states. The JPD provide a probability for each possible combination of values of all variables. If the JPD is known, the posterior probabilities given an observation can be calculated. However, the calculation of the JPD becomes intractable with the increase of the variables included in the model. The key to efficient representation of

JPD is to reduce the number of probabilities that are involved. This is achieved with the introduction of conditional independence. This states that a variable is independent of all its non-descendants given its parents. This factors the JPD into several component distributions that is easier to compute because they depend on smaller set of variables. This property of BBNs is realised with the use of directed acyclic graphs and their corresponding CPTs. In the above example, the conditional probability of the accident's risk given the characteristics of the road design and the driving behaviour is quantified in the CPT as shown in Table 1.

Table 1. A conditional probability table for the BBN model in Figure. 2

	Road Design	Bad		Good	
	Driving Behaviour	Bad	Good	Bad	Good
Accident	Major	0.76	0.4	0.6	0
	Minor	0	0.6	0.4	1

Column 1 asserts that if the Road Design is "Bad" and the driving behaviour is "Bad", then the probability of a major accident is 0.76, with zero probability of being a minor accident. CPTs are configured by estimating the probabilities for the output variables by an exhaustive pairwise combination of the input variables. Conditional probabilities can be estimated based on subjective judgements (elicited from domain experts) or inferred from hard data (Pearl 1988). When the network and CPTs have been completed, Bayes' formula is used to calculate the posterior probability of each state of each node in the network using input from the JPD. The Baye's theorem is shown in equation 1:

$$P(a/b) = \frac{P(b/a)P(a)}{P(b)} \quad (1)$$

where, *P(a/b)* = posterior (unknown) probability of *a* being true given *b* is true, *P(b/a)* = prediction term for *b* given *a* is true (from JPD), *P(a)* = prior (input) probability of *a*, *P(b)* = input probability of *b*.

Input evidence values are propagated through the network, updating the 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. BBN models are extremely computation-intensive; however, recent propagation algorithms exploit graphical models' topological properties to reduce computational complexity (Pearl 1988). These are used in several commercial inference engines such as HUGIN, which we used.

5 BBN MODEL FOR ACCIDENT RISK ASSESSMENT

Based on Hollnagel's (1998) classification of accident risk assessment techniques, our method combines epistemological and sequential perspectives and employs influences from safety, reliability and human performance theories for the development of the accident risk assessment model. Mental workload constitutes an important influencing factor to road safety that is directly related to human performance (Megaw 2005)(Wickens 2002) and situation awareness (Endlsey 1995). According to Rouse (1993), workload is defined as the demand placed upon people which may be a behavioural response to events, communication and interaction between the humans and technology. Wickens (2002) portray workload as the cost of accomplishing task requirements for the human element of socio-technical systems. High levels of workload degrade the operator's concentration, information processing and decision making, leading to increased errors which might have catastrophic effects (Wickens 2002)(Reason 2000) (Leveson 1995). Workload assessment falls into three main categories (Megaw 2005): (a) performance-based measures (b) subjective measures and (c) physiological measures. The performance measures concentrate on the assumption that an increased task demand is translated into decreased human reliability, due to increased workload, which subsequently decreases concentration and increases errors. Situation awareness according to Endsley (1995), is the process of understanding the world with some aspect of future projection. In the case of the road network this corresponds to the understanding of the activities of other drivers, the road network conditions, the weather etc. This activity is directly related to mental workload and information processing which when increased have an adverse effect on it (Endsley 1995). The principal component of information processing is the notion of attention. Humans coordinate perception and cognition using a set of mechanisms that enable perceptual attention. Humans need perceptual attention because there is simply too much information in the visual field for the perceptual system to process. Wolfe (1994) points out that there are two ways of dealing with this problem. The first way is to ignore excess information. The second way is to be selective in processing the information that is sensed. In the case of road accidents, when the information that needs to be processes by the driver exceeds his/hers available cognitive capacity, this results in increased workload, reduced situation awareness and subsequently increased errors.

For the development of the accident risks BBN topology (Figure. 5) we firstly identified the causes associated with road accidents. These causal factors were identified through initial literature review on accidents causations and probabilistic assessment of human error :ATHEANA, HEART, CREAM, THERP, SAGART (Hollnagel 1998)(Swain 1983)(Kirwan 1998). The identified causes constitute the accident shaping factors affecting the operator's actions. The model as depicted in figure 5, is composed of four categories which describe properties of the vehicle, the environment, the road and the driver. Vehicle properties include usability, reliability, functionality, maintenance, in-car entertainment etc. Poor vehicle features have an adverse influence on mental workload and stress (Grabowski et al 2003). The environmental context addresses weather conditions and properties of the road network. These according to Bailey (Bailey 1996) have an indirect influence on an individual's stress through increased fatigue. Moreover, environmental influences have a negative effect on an individual's workload (Wickens 2002). Finally, the driver's properties, such as inherent ability, training and experience, affect his/her capability by acting as antidotes to stress. Hence, adequate training and experience could act as resistors to increased stress and normalisers to human reliability. The model also addresses issues that relate to driving behaviours as they have been are identified through an initial accident reports analysis and past Police surveys. This constitutes a subcategory of the driver influencing factors. Input to the BBN is obtained from the road network simulator. Traffic information for different sections of the road network is obtained via the "Observer" component of the software agent platform, and subsequently supplied to the accident risk assessor for quantification. Results from the risk assessors are visualised on the simulation model.

6 RESULTS

Preliminary results from this research address the development and validation of the BBN model for accident quantification. After obtaining data from Police accidents reports we pursued to analyse these through an initial relevance analysis, a technique stemming from the data mining domain. This helped us reduce the dimensionality of the problem, and concentrate on the principal factors affecting accident risk. Further dependency analysis through the application of the association-rules technique, among available parameters assisted the development of an initial structure that helped as to create a taxonomy of the principal accident influencing factors and their interrelationships. Combination of these and identified influences from the literature review yielded the topology of the BBN model depicted in figure 5. Our main challenge during the development of BBN was the population of the conditional probability tables (CPT) that define the prior knowledge embedded in the model. This constitutes a major limitation of BBN technology and is an active area of research (Druzdzel 2000). In our case we use two techniques for generating the CPTs. Firstly; we analysed the historical data of road accidents in as they have been obtained from the Police. With the use of the Expectancy Maximization algorithm, we managed to generate CPTs for parts of the BBN model that the data described. For the part of the BBN model that describe the human performance influences we used results from the human error literature (Swain 2000)(Reason 1983). The accident probabilities for each influencing factor were based on the THERP database of human error probabilities included in chapter 20 of the techniques handbook (Swain 1983) and the weighting factors of the Error Producing Conditions (EPC) of the HEART method (Williams 1988). Once the accident risk probabilities had been decided for the human performance part of the model, we used the Noisy-Max method (Díez 2003) to generate the CPTs. Remaining CPTs were populated using subjective estimated from Subject Matter Experts (SME) and the application of the Noisy-Max approach that eases the data acquisition problem when experts are involve by requiring fewer probabilities.

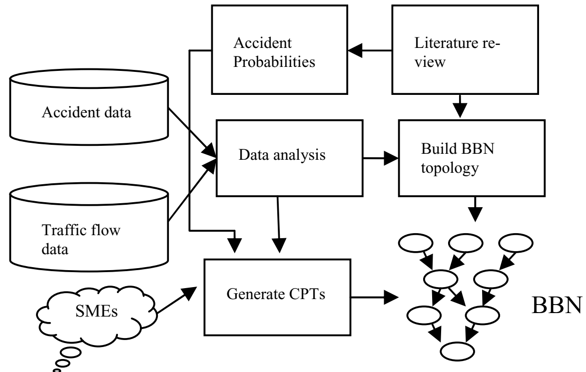

Figure 3. BBN model development

Further analyses were conducted to calibrate the CPTs and BBN model topology. Specifically, based on 8000 records of police accident reports we identified critical manifested factors that when occurred in combination with poor network design, environmental conditions and driver performance leaded to accidents. The frequency distributions for each of those factors are depicted in figure 4 and correspond to the influencing factors of table 3. Each bar corresponds to the frequency of one manifested accident factor. Results show that fatal accidents main causes are: unsafe speed, inattention and inappropriate overtaking. The last two are attributed to reduced situation awareness while the latter in combination with reduced situation awareness is disastrous. Major accident statistics also indicate the importance of situation awareness, while minor accidents stress the importance of improper driving behaviour as this is described by the car following model that explicitly state the minimum safe distance between two moving vehicles.

Table 2 driver action prior to accident

	ACTION BEFORE ACCIDENT
1.	GOING STRAIGHT AHEAD
2.	MAKING RIGHT TURN
3.	MAKING LEFT TURN
4.	MAKING U TURN
5.	STARTING FROM PARKING
6.	STARTING IN TRAFFIC
7.	SLOWING OR STOPPING
8.	STOPPED IN TRAFFIC
9.	ENTERING PARKED POSITION
10.	PARKED
11.	AVOIDING OBJECT/POTHOLE IN ROAD
12.	AVOIDING PEDESTRIAN IN ROAD
13.	AVOIDING VEHICLE IN ROAD
14.	CHANGING LANES
15.	OVERTAKING
16.	MERGING IN MOTORWAY (ACCELERATION LANE)
17.	DIVERGING IN MOTORWAY (DELERATION LANE)
18.	BRAKING

These results were used to adjust the weighting factors for a subset of the model's accident causes, during the parameterisation of the CPTs through the Noisy-Max method. Similarly the action of the driver prior to the accident (table 2) were also analysed to produce the frequencies used for calibrating the impact of driving behaviour to accident risk. This information is also obtained from police reports.

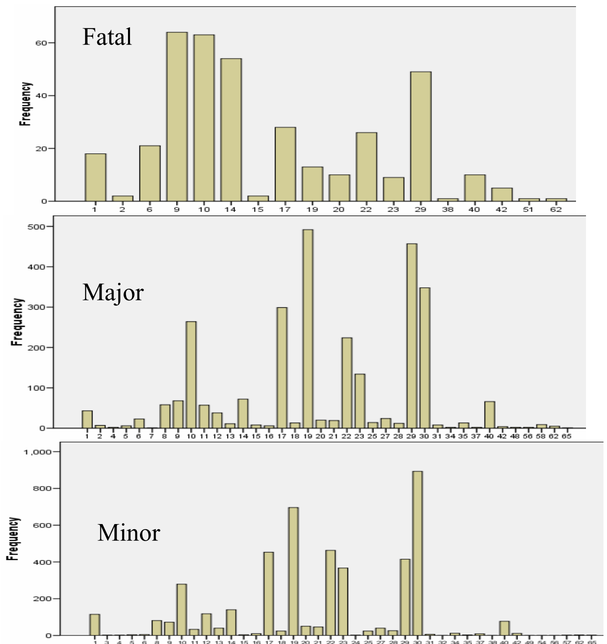

Figure 4. Frequencies of accident categories by contributing factors on X-axis

Table 3. List of influencing factors

	HUMAN
1.	ALCOHOL INVOLVEMENT
2.	DRUGS (ILLEGAL)
3.	PRESCRIPTION MEDICATION
4.	SUDDEN ILLNESS
5.	LOST CONSCIOUSNESS
6.	FELL ASLEEP
7.	PHYSICAL DISABILITY
8.	DRIVER INEXPERIENCE
9.	UNSAFE SPEED
10.	FAILURE TO KEEP TO NEAR SIDE
11.	FAILURE TO KEEP TO PROPER TRAFFIC LANE
12.	LANE CHANGING (IMPROPERLY)
13.	OVERTAKING IMPROPERLY ON NEAR SIDE
14.	OVERTAKING IMPROPERLY ON OFF-SIDE
15.	CUTTING IN
16.	FAILURE TO STOP/ALLOW PEDESTRIAN CROSSING
17.	FAILURE TO GIVE RIGHT-OF-WAY
18.	TURNING LEFT WITHOUT CARE
19.	TURNING RIGHT WITHOUT CARE
20.	MAKING U TURN
21.	BACKING UNSAFELY
22.	TRAFFIC SIGN DISREGARDED
23.	TRAFFIC SIGNALS DISREGARDED
24.	POLICE SIGNAL DISREGARDED
25.	CROSSING WITHOUT CARE AT UNCONTROLLED JUNCTION
26.	FAILURE TO SIGNAL PROPERLY
27.	PULLING OUT FROM NEAR SIDE
28.	PULLING OUT FROM OFF-SIDE
29.	DRIVER INATTENTION/ DRIVING WITHOUT CARE
30.	FOLLOWING TOO CLOSELY
31.	STOPPING SUDDENLY
32.	SWERVING/RUNNING OFF THE ROAD OUT OF CONTROL
33.	DAZZLED BY LIGHTS OF OTHER VEHICLE
34.	DRIVER OPENING SIDE DOOR
35.	OTHER ERROR ON BEHALF OF DRIVER
36.	DRIVER HAMPERED BY PASSENGER,
37.	ANIMAL, OR LUGGAGE
38.	PASSENGER OPENING SIDE DOOR
39.	BOARDING OR ALIGHTING BUS WITHOUT CARE
40.	OTHER ERROR ON BEHALF OF PASSENGER
41.	PEDESTRIAN CROSSING WITHOUT DUE CARE
42.	PEDESTRIAN IMPROPERLY USING PEDESTRIAN CROSSING
43.	OTHER ERROR ON BEHALF OF PEDESTRIAN
	VEHICLE
44.	BRAKES DEFECTIVE
45.	HEADLIGHTS DEFECTIVE
46.	REAR LIGHTS DEFECTIVE
47.	OTHER LIGHTING DEFECTIVE
48.	STEERING FAILURE
49.	TIRE/WHEEL FAILURE
50.	TOW HITCH DEFECTIVE
51.	OVERSIZED VEHICLE
52.	OVERLOADED VEHICLE
53.	OTHER VEHICULAR FACTOR
	ENVIRONMENTAL
54.	LANE MARKING IMPROPER / INADEQUATE
55.	TRAFFIC SIGNS IMPROPER/INADEQUATE
56.	TRAFFIC SIGNALS IMPROPER/NOT-WORKING
57.	OBSTRUCTIONS/DEBRIS ON ROAD
58.	PAVEMENT DEFECTIVE
59.	PAVEMENT SLIPPERY (CONSTRUCTION)
60.	SHOULDERS DEFECTIVE
61.	GLARE (ROAD SURFACE)
62.	VIEW OBSTRUCTED/LIMITED
63.	PAVEMENT SLIPPERY (WEATHER)
64.	STRONG WIND
65.	SUN GLARING
66.	ANIMAL ACTION
67.	OTHER ENVIRONMENTAL FACTOR

Once the BBN model had been developed we conducted a preliminary validation study. Results from this study demonstrated satisfactory level of accuracy. Initially we analyzed accidents in road networks that have been attributed to Human Unreliability as were described in Police accident reports. Subsequently we used properties of these accident scenarios in combination with their identified causes to validate the BBN model. This technique enabled us to test whether the model would generate predictions similar with the known scenario outcomes. Accident scenarios were categories into fatal, major and minor. From the 10 fatal accident scenarios, the BBN model demonstrated consistent level of accuracy. Additional 10 major accident scenarios, revealed medium level of accident risk while minor accident scenarios yielded low level of accident severity. Collated results of our initial model validation are depicted in table 4. Intersection between rows and columns of similar scenario types indicate the average estimated accident likelihood from the BBN runs. It is evident from the table that the model produces estimates similar to known scenario results. Therefore based on table 4, when a number of fatal accident scenarios were used to test the BBN model, this produced probabilities of fatal accident with mean value of 0.92. Similar results were obtained for the major and minor accident types.

Table 4- BBN Validation results

Known scenario outcome	Minor	0.04	0.05	0.91
	Major	0.01	0.86	0.13
	Fatal	0.92	0.08	0
		Fatal	Major	Minor
	BBN Estimates			

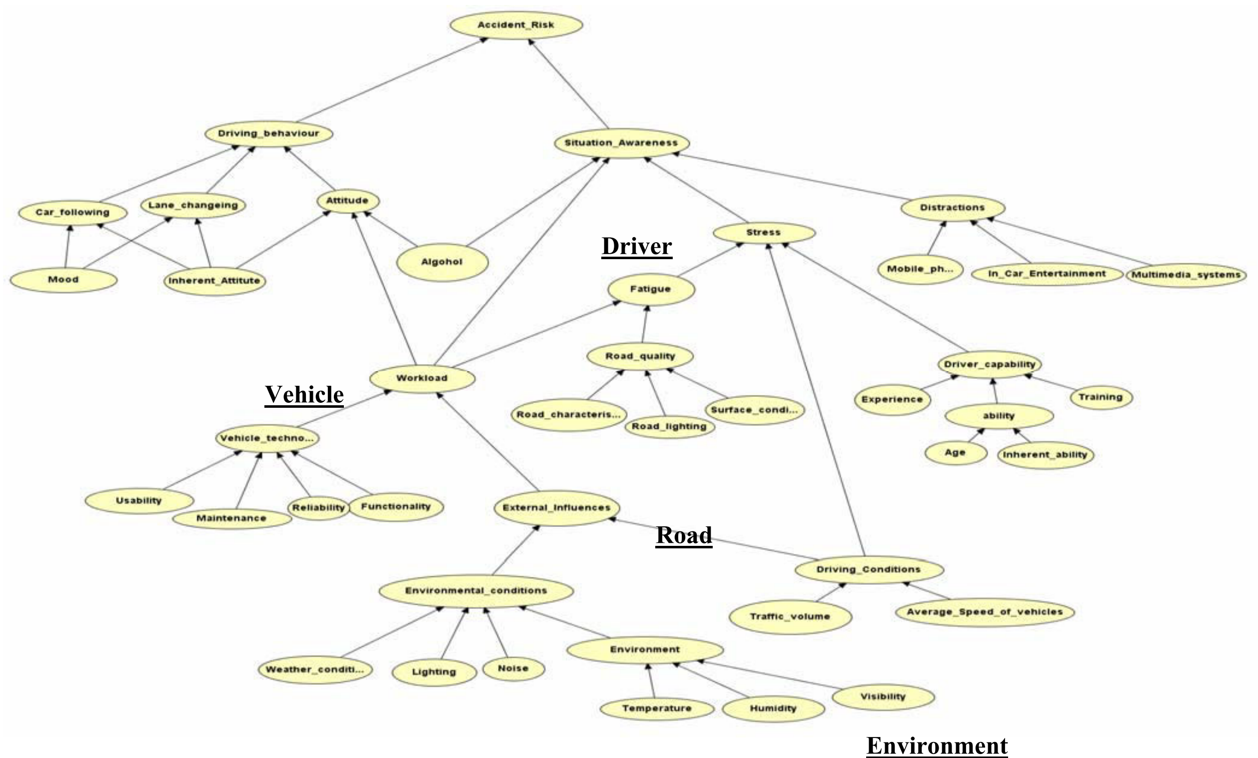

Figure 5 Accident risk assessment BBN model topology

7 DISCUSSION

Results from contemporary road accident analyses conclude that the human element constitutes an important parameter that contributes towards accidents. Human unreliability is attributed to our limited cognitive capabilities and the increase demand for information processing during vehicle navigation. Driver’s information processing demand change with respect to the design of the road network, the traffic volume, the technology used inside and outside the vehicle, the weather conditions and the tasks performed by the driver while navigating the vehicle. The literature (Reason 2000) warns that increased demand for cognitive resources increases the likelihood of committing an error. Therefore, road networks should be designed not solidly on engineering principles by also on Human Factors analyses. The introduction of new technologies in vehicles (GPS, collision avoidance), or in the road network (intelligent highways) increases the demand for driver’s attentional resources, which when reached or exceeded, decreases situations awareness that could lead to accidents.

The approach described in this paper, is based on the combination of Bayesian Belief Networks (BBN) and microscopic road network simulation in accordance with agent-base technology for real time assessment of road accident quantification. The BBN model we developed assesses the likelihood of an accident occurring on the road network based on real time information obtained from the simulation. The BBN model is developed on a multi disciplinary principles and its input includes but not limited to: traffic volumes, road network characteristics, weather conditions, and driving behaviours. The microscopic simulator enables the visualisation of emerging traffic scenarios. Software monitoring agents capture and process information from the simulation and provide these to the risk assessor in real time to quantify accident likelihoods. BBNs have also been used for road safety performance assessment by (Simoncic 2004) and (Hu 2004). However, their efforts focuses on the development of the BBN model rather than its use and the context of the analysis is narrower. Following the initial success of our BBN model validation during the first phase of our project we are now in the process of validating our preliminary simulation model that mimics a section of a road network in Cyprus, using statistical data obtained from the department of Public works. Subsequently, we will augment this model with driving behaviours obtained from ethnographic surveys and Police research. For the scenario generation process, we are developing a knowledge representation of road accident causations which in combination with Monte Carlo sampling will generate a sufficient set of plausible scenario variations to stress test current of prospective road networks.

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