Application of a Bayesian network to aid the interpretation of blood alcohol (ethanol) concentrations in air crashes

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Abstract

In the investigation of a fatal air crash, it is important to determine if the pilot, at the time of death, was contravening the regulations in relation to 1) the permitted concentration of ethanol (alcohol) in the blood and 2) whether the pilot had consumed alcohol within a specified period before flying. It is also important to assess whether any alcohol detected in the toxicological samples was present either because of consumption or because of post-mortem alcohol formation. We have developed a Bayesian Network that models the relationships between analytical results, circumstantial evidence and the concentration of alcohol at the time of death in cases of air crash. The model provides a rational, coherent approach to forensic interpretation, moving interpretation from a largely subjective, generalist approach to a more objective, case-specific methodology utilising available relevant data and accommodating the inevitable uncertainties within a case.

Keywords

Bayesian network, ethanol interpretation, air crashes, postmortem,

Introduction

Forensic Toxicology is an area of forensic science that provides evidence to help fact finders assess the role of drugs either on a person's behaviour (e.g. as in intoxication or sports performance enhancement) or on their survival (e.g. as in death investigations) [1]. With the advent of modern analytical techniques, it is possible to determine with validated methods both the identity and concentration of drugs that may be found in body fluids and tissues[2]. Forensic practitioners are required to interpret the results of those analyses in order to help the fact-finder or decision-maker (such as the police, forensic pathologist, coroner or court) to form a conclusion on the impact of the drugs on the individual being investigated. Conventionally, interpretation by forensic toxicologists has been subjective, based on the individual toxicologist's knowledge and experience, and the basis of that opinion may not have been fully transparent to the receivers and users of the opinion [3,4]. This approach to interpretation, as in other areas of forensic science, could be considered a significant limitation of practice, especially after the call for greater objectivity in forensic interpretation following the NAS report in 2009 [5]. Furthermore, toxicological interpretation has been largely a description of the generalities of the effects of drugs rather than being a case-specific interpretation. Interpretation of forensic toxicological evidence needs to move from this largely subjective, generalist approach to one that is more objective in nature and which accommodates the inevitable uncertainties, such as limited data-sets and incomplete knowledge of circumstances, that are involved in case-specific interpretation.

The application of a methodology called Bayesian Networks to forensic science problems has grown over the last twenty years [6]. Bayesian Networks provide a logical and transparent means of combining evidence, both expert and circumstantial, to arrive at a justifiable conclusion. While not yet presented as evidence in court (to the authors' knowledge), Bayesian Networks are proving helpful to forensic scientists in mapping out and understanding the logical relationships between the variables in a case and in utilising whatever relevant data there may be [6]. The benefits of Networks include 1) the display of the probative force of separate pieces of evidence, 2) modelling the impact of individual and combined pieces of evidence, 3) assessing the probability of the truth of the issues in question given the combination of evidence, and 4) offering a means of transparent communication of reasoning [7–9].

While the use of statistics and probability in forensic science is not new, the use of statistics and probability in a formal inferential framework is only just emerging in forensic toxicology. For example Fuller *et al* [10] presented a "causality index" to compare incidental and lethal post-mortem drug concentrations using inferential statistics , Langford *et al* [11] described a

Bayesian Network for the assessment of the probability of a death having been caused by the analytically determined blood concentration of drug(s). Biedermann *et al* [12], Taroni *et al* [13]and Bossers & Paul [14] used likelihood ratios for the interpretation of forensic cut-offs and legal thresholds and Woldegebriel *et al* [15]used Bayesian algorithms for the detection of compounds during unknown drug screening.

Bayesian Networks have significant potential across the whole range of forensic toxicology casework. However, given the current understanding of, and expertise in, the use of such networks within the discipline, the present work focusses on just one type of case in an attempt to develop a robust, justifiable model of the variables and their relationships, thereby assisting the evolution of applications in forensic toxicology. The case-type chosen for this work is that of fatal crashes of aircraft. A key toxicological issue in this type of case is generally whether the ethanol (alcohol) concentration in the pilot's blood at the time of flying was above or below a statutory limit as set out in the regulations of the relevant aviation authority [16]. For example, the regulations of the Federal Aviation Authority (FAA) of the United States restrict pilots from "flying or attempting to fly an aircraft within 8 hours of consuming alcohol or if they have an alcohol concentration of 0.04 percent or greater," Pilots may not use alcohol "while on-duty or within 8 hours of performing flight crew member duties" (14 CFR § 91.17 - Alcohol or drugs). However, there is no single regulation that covers all countries - each country or region being free to set its own permitted level. In the European Union (EU), the permitted alcohol concentration is lower, 0.02%, than that for the FAA [17] .

This paper will begin by describing briefly the architecture of Bayesian Networks (fuller, more authoritative, descriptions being available in the references previously quoted) and will then present a case-specific network for the alcohol concentration in a pilot's blood. We will utilise published data to populate the probability tables of the nodes of the network and, where such data are not available, we will make informed expert judgements in assigning such probabilities.

Bayesian Networks

Bayesian Networks are graphical, visual representations of the uncertainties in a case and their relationships; they facilitate the combination and weighing of separate pieces of evidence to arrive at a probability of the truth of a fact in issue

The uncertainties (or variables) are depicted by "nodes", and the relationship between nodes is represented by a directed arc (or arrow). Because a node represents an uncertainty, such as, for example, "cause of death", it encompasses a number of potentially true "states". As

we will see later, each state will have an assigned probability of occurring. Assigning probabilities is a topic that stimulates much discussion [18] but, for the purposes of this paper, we will proceed on the basis that all probability assignments are conditional - some assignments will be conditioned fully on research and survey data while others will be conditioned on more personal knowledge gained through study and experience. In the complete absence of any information or knowledge to help assign a probability, then the probability space can be equally divided between all the possible states – a condition known as maximum uncertainty. Irrespective of how probabilities are assigned, it is imperative that the assigner makes clear the basis of how they have arrived at a value.

A node that is at the start of an arrow is called a "parent" node and the node at the end is called a "child" – the state of the child node is dependent on the state of the parent node. Therefore, probabilities for the states within child nodes are conditioned not only on the assigner's knowledge (as mentioned earlier) but also on the state of the parent node. We will use tables to depict the conditional probabilities contained within in each node.

Note that it is preferable for the possible states of a node to be exhaustive and mutually exclusive such that their probabilities sum to 1.

Commercial and open-source software is available for constructing and using Bayesian Networks such as GeNIe (Bayesfusion.com); Hugin Expert (hugin.com); the Python package PyMC3 and bnlearn package for R. For the network illustrated in this paper we utilised GeNIe 2.2 Academic.

For a more in-depth review and explanation of Bayesian Networks and their application in forensic science, we direct readers to Taroni *et al.* [6].

Case-specific network

Of all the possible case examples in toxicology that could have been selected for this exploratory paper, we have selected the issue of alcohol levels in aircraft pilots who had died in aircraft crashes. We believe this represents a relatively straightforward situation but one which combines circumstantial as well as scientific evidence. The network we present is our best assessment of the key variables and their connections as well as what we consider are the most relevant published data that we could find. We do not assert that it is the "best" network or that we have included all the significant variables and relationships. We do believe, however, that it does provide a starting point for practitioners who may wish to contribute to the development of more robust, helpful networks in this and other case types or for researchers whose work may help improve the probabilities contained in each node.

The following are the hypothetical case circumstances.

A commercial passenger aircraft crashed at midday on 1st July 2019 in a field in the centre of the United States of America. All passengers and crew were killed. Postmortem samples were taken from the pilot approximately 3 days after the crash. The regulatory fact in issue in the case (assuming FAA rules apply) is whether the pilot had consumed alcohol within 8 hours of flying and/or whether the pilot was equal to/above or below a 0.04 % blood alcohol concentration at the time of flying. While various analytical tests are available and various samples may be taken to assist in the determination of alcohol consumption and its concentration, often not all of these tests will be applied in all cases, due to the state of the body and other factors [19]. For this hypothetical case, we have included nodes for the more commonly utilised tests to illustrate how the results of these tests may be combined logically. The samples that are recommended to be taken (as a minimum) are vitreous fluid, urine, blood (femoral), brain and muscle [20], with the analysis of these samples for ethanol, other volatiles in all samples and 5-hydroxytryptophol (5HTOL) and 5-hydroxyindoleacetic acid (5HIAA) in urine [20,21]. 5-HTOL and 5-HIAA are metabolites of the neurotransmitter serotonin. The ratio of the quantities detected of 5-HTOL to 5-HIAA is elevated when alcohol is consumed and metabolised, with the ratio remaining elevated for 8 hours after consumption [22].

We have also included nodes for aspects of the case circumstances that may be considered as having an impact on the fact in issue. The developed Bayesian network is shown in Figure 1.

Explanation of the nodes and their conditional probability tables.

The following acronyms are used throughout.

VAC – vitreous alcohol concentration

BAC – blood alcohol concentration

UAC – urine alcohol concentration

VOC – volatile organic compound

TOD – time of death

PMF – post-mortem alcohol formation

5-HTOL - 5-hydroxytryptophol

5-HIAA - 5-Hydroxyindoleacetic acid

Each node will be shown in all figures in this paper as having mutually exclusive, exhaustive, discrete states. The use of discrete states is a less than optimal approach, given the continuous nature of some of the variables (such as BAC), but in order to keep the network relatively manageable in this initial stage of its development, we have chosen this 'discrete' approach for all nodes.

Node 6 – Ethanol consumption within eight hours of death

This node represents the primary fact in issue, i.e. the primary uncertainty for the fact-finder. It is shown as the parent to three other nodes: node 3 - Witness evidence of alcohol consumption; node 5 – Blood alcohol concentration at time of death; and node 9 - 5-HTOL: 5-HIAA ratio.

Data from Botch & Johnson (2008) show that "from the 2,391 aviation accidents evaluated during the examined time period the percentage of all pilots with ethanol concentrations above 40 mg/dL at the time of the accident was approximately 5%" [23]. Despite the fact that these data are from pilots who had previous drug or alcohol offences, we have adopted the 5% figure as a starting value for the probability of ethanol consumption within 8 hours of death. The probability table for this node is given in figure 2. If there is any information from the case circumstances that would inform a more realistic probability, then that should be taken into account when assigning a value to the probability. For example, if there is very strong evidence that pilot had very rarely consumed alcohol, then that may well suggest a much lower probability than 5% should be assigned.

Node 3 – Witness evidence of alcohol consumption

This node is depicted as a child of node 6 because the probability of witness evidence of alcohol consumption would seem to be dependent on whether alcohol had or had not been consumed in the relevant time span.

In the absence of any case-specific information, if there had been alcohol consumption within the previous 8 hours, we believe that maximum uncertainty, in this instance 0.5 for both states, would be appropriate for the probability of witness evidence of consumption. Data on, for example, the proportion of deceased pilots who, having measurable BAC, also had witness evidence of alcohol consumption would be very helpful in assigning probabilities.

If there had been no alcohol consumption, we believe there would be a very low probability of any witness evidence of consumption. We have assigned an indicative value of 0.001.

These values for the probabilities are, of course, open to discussion and amendment because they are very much personal, subjective probabilities. There are no published data, as far as we are aware, that would help us assign more justifiable probabilities. The probability table for this node is given in figure 3.

Node 5 – Blood alcohol concentration at time of death

As with node 1, this node captures another key uncertainty that the fact finder has to resolve. It is shown as dependent on whether alcohol had been consumed within 8 hours of death. Note that, unlike the nodes already described, there is not a binary choice of states for this node. In reality, this is the type of node for which a continuous distribution of values would be appropriate. However, given the limitations of the mathematical basis of the network, and the structure of the data, we have adopted discrete values of BAC (Negative, 10-19 mg/100ml, 20-29 mg/100ml, 30-39 mg/100ml, 40-49 mg/100ml, 50-80 mg/100ml, 80 – 100 mg/100ml, and >101 mg/100ml).

Given the condition that a person had not consumed alcohol (condition = 'No'), we have assigned a high probability of 0.93 for the state 'negative BAC'. The remaining probabilities under this condition have been evenly distributed among the remaining states, reflecting our maximum uncertainty about observing each of these states.

If alcohol had been consumed (condition = 'Yes'), we have to ask – what information would inform our probability of observing the various concentrations of alcohol in this particular case? Data on the proportion of pilots who have consumed alcohol and who had positive BAC just before flying could be used to assign general, initial probabilities for the different states but it must be borne in mind that general probabilities may not be appropriate for an individual case. In any event, we have been unable to source such pilot data and, therefore, we have assumed that, if the pilot had consumed alcohol, the level of alcohol was more likely to be above 50 mg/100ml but would peak at 80-100 mg/100ml. This assumption could be challenged and the assigned probabilities could be amended to reflect fuller knowledge either about concentrations generally in pilots or about this pilot in particular. In the absence of any knowledge whatsoever, uniform probabilities could be assigned to reflect maximum uncertainty for all possible states. The probability table for this node is given in figure 4.

Node 9 - 5-HTOL: 5-HIAA ratio

This node is dependent on Node 6, Alcohol consumption within previous 8 hours,

Voltaire *et al* (1992) provides data on the ratio of the two markers 5-HTOL:5HIAA in urine [24]. The mean value of 5- HTOL:5-HIAA in a group of 69 persons abstaining from alcohol was 7.6 (pmoles 5-HTOL/nmoles 5-HIAA). Ninety-seven percent had ratios ranging from 4 to 17, with no value exceeding 20. A group of healthy volunteers were tested 12 hr after alcohol consumption and showed a dose-dependent and statistically significant elevation in the 5-HTOL/5-HIAA ratio. Four regular alcohol consumers who were followed during a period of 3 months of drinking had elevated values of the 5-HTOL/S-HIAA ratio in 60% of their urine samples. It would seem that a 5-HTOL:5-HIAA ratio above 15 (pmoles/nmoles) would be highly probable given recent alcohol consumption and we have assigned therefore an indicative value of 0.999 for observing such a ratio under this condition (condition = 'YES'). If there had not been any recent alcohol consumption (condition = 'No'), we have assigned a probability of 0.001 for the state of 'above 20'. It should be stressed that the probability values under the condition of Yes' are not related to those under the condition of 'No' – it is coincidental that they appear complementary. The probability table for this node is given in figure 5.

Node 8 – VAC +ve (>10mg/100ml)

This node is shown as dependent on node 5, BAC at time of death. The two states of the node are 'Positive', i.e. above 10mg/100ml, and 'Negative', i.e. below 10mg/100ml.

To assign initial conditional probabilities for these two states, we have relied on data from Levine *et al* (1993) to inform the probability of vitreous alcohol concentration (VAC) being positive (>10 mg/100ml) conditioned on the level of BAC [25]. This study investigated a series of 381 cases where ethanol was detected in blood at concentrations <50 mg/100ml and also measured BAC in vitreous samples and urine. In cases where BAC was 10 mg/100ml 55% cases were +ve for ethanol in vitreous (VAC >10 mg/100ml), this increased to 59% with a BAC of 20 mg/100ml, 70% when BAC was 30 mg/100ml and 90% when BAC was 40 mg/100ml. Above 50mg/100ml BAC all vitreous samples were positive for ethanol. The probability table for this node is given in figure 6.

Node 7 – UAC +ve (>10mg/100ml)

This node is shown as dependent on node 8 (VAC) because knowledge of the state of node VAC would inform our expectations for the state of node UAC. The reverse is also true – knowledge of the state of UAC would influence our expectations for the state of VAC – and, therefore, an alternative model would be feasible.

There are two possible states – Positive', i.e. above 10mg/100ml, and 'Negative', i.e. below 10mg/100ml. The value of <10mg/100ml is commonly considered as a 'negative' VAC.

All initial probabilities for this node are based on data in Levine *et al.* (1993)[25]. That paper provides data to inform the probability of urine alcohol concentration (UAC) being 'positive' (>10 mg/100ml) given the detection of ethanol in VAC at BAC below 50 mg/100ml. Above 50mg/100ml BAC all UAC and VAC samples were positive. The probability table for this node is given in figure 7.

Node 1 – PM alcohol formation (PMF)

Alcohol may be produced naturally after death due to fermentation of sugar(s) in the body in the body by microorganisms such as bacteria and fungi. The amount of alcohol produced will depend on environmental conditions, such as temperature and humidity, and on the elapsed time between death and sampling, but to date is not predictable [21] . Reliable data in the published literature to inform the probability that PMF has occurred in a cadaver is limited: PMF in a cadaver has been assumed to have occurred if other tests such as VOC, UAC, BAC and VAC point towards it. However, there is no single test, or combination of tests, that will confirm categorically that PMF has occurred and, therefore, there can be no data set based on known PMF cases from which to assign probabilities.

The prior probability for the presence, in any one case, of PMF will be dependent initially on the case circumstances. For example, if a sample had been taken from a body within a very short period of time, and the environmental conditions were cold and dry, then the probability of PMF may be quite low. If, however, the sample had been taken several days after death and the conditions were hot and humid, then that probability may be high. For the purposes of this paper, and in order to accommodate maximum uncertainty, the initial probabilities for the two states in the node's table, i.e. 'PMF' and 'no PMF', have been set as 0.5 each. The probability table for this node is given in figure 8.

Node 2 – Volatile organic compounds (VOC) detected

Node 2 is shown as a child of node 1 because the detection of VOC will be dependent on the presence or absence of PMF. The conditional probabilities under "No PMF" are based on data from aircraft accidents reported by Canfield *et al* In those cases in which PMF was deemed NOT present, because no alcohol was detected in the blood, VOCs were detected in 9 of 22 deaths, i.e. 41% [26].

Although there were also data from "PMF" cases, these cases were inferred as such from other analytical data. Therefore, as described for Node 1, it was decided to use maximum uncertainty because of the lack of reliable data. The probability table for this node is given in figure 9.

Node 4 – Analytically measured postmortem BAC

For this node, we have adopted the same discrete distribution of possible states as in node 5, 'Blood alcohol at time of death'.

With no post-mortem alcohol formation (condition = 'NoPMF'), we have assumed that the measured BAC would very probably (0.93) be the same as the BAC at the time of death. The remainder of the probability space has been distributed evenly among the remaining categories but this distribution could be refined.

For the probabilities under the condition 'PMF', specifically for the 'negative' column for 'BAC at time of death', we took the BAC that had been measured in 3 papers (Mayes *et al*[27], Gillan & Bost [28] and Zumwalt *et al*[29]) where it was confirmed no alcohol had been consumed before death and all alcohol detected was deemed due to postmortem formation. We combined the data from the two papers and produced a table based on the states as defined in the node table (see figure 10). However, the shape of the distribution of probabilities looks unusual and would suggest that an increase sample size would improve the probability table in this node.

For the remainder of PMF group, we assumed on average there was a 30mg/100ml increase in measured BAC due to PMF over and above the level of alcohol that would be due to consumption and adjusted the probabilities accordingly. The probability table for this node is given in figure 11.

Discussion

The software package used to compile the network allows users to instantiate any of the nodes and to observe the effects on the posterior probabilities of the two key facts in issue - the probability that the pilot was above the permitted blood alcohol concentration at the time of death and the probability that the pilot had consumed alcohol within 8 hours of flying.

Figure 12 shows the probability states of the network with no evidence. The width of the arrows indicate the strength of the evidence provided by the child node to the parent node. These depictions allow the "importance" of each node to the network to be seen. Node 2 (VOC detected) has very little influence on the network because the likelihood ratios are ~1 and therefore the arrow is thin in width. The analytical information provided by VOC is of little importance when determining the probability of a pilot having consumed ethanol and being above the statutory limit. As expected, the measurement of BAC, VAC, UAV and 5-HTOL/5-HIAA ratio have the greater importance.

In order to demonstrate the potential effectiveness of the Bayesian network in aiding interpretation of blood alcohol concentrations in air crashes we compared the results from the Bayesian network in this work to published interpretations by Johnson *et al* [30] of 5 cases of air crashes where the potential consumption of ethanol was in question and toxicology was performed. The figures 13 to 17 show the probability of the network nodes given the evidence outlined in Johnson *et al.* [30] and summarised in table 1. Nodes 5 (BAC at the time of death) and Node 6 (ethanol consumption within 8 hours of death) are the important output nodes for a decision of antemortem alcohol consumption and a BAC above the relevant statutory limits. The results from the network do not contradict the decisions in the published work but do show that, instead of categorical decisions about whether alcohol was from post mortem formation or from consumption and about whether a pilot was above or below a statutory limit, a Bayesian result provides a more nuanced opinion that rightfully leaves the final decision to the fact finder not the expert. For example, in case 3, the network give the possibility that there is a 58% probability that the BAC at time of death was negative but also there is a 38% probability that the BAC at the time of death was between 20 and 29 mg/100ml. In cases 1,2 and 5, where the evidence from both the net and the Johnson *et al study* indicate that the alcohol detected was from postmortem formation, the probabilities of a negative BAC at the time of death are between 89-91% but there is a residual small chance (11-9%) that the ethanol detected was due to consumption. Due to the large likelihood ratios provided by the probability values in node 9 (approx. 1000 and 1/1000), this node has a large influence over the posterior probabilities in node 6 (ethanol consumption within 8 hours of death). When instantiated, the analytical evidence of the 5-HTOL/5-HIAA ratio produces, in this network, posterior

probabilities of either 0% or 100% for node 6 (ethanol consumption within 8 hours of death). Such categoric probabilities, amounting to the inferences that either the pilot definitely has not (0%) or definitely has (100%) consumed alcohol is probably a result of rounding of extreme values of posterior probability and is not what we have expected. Further study data for node 9, and also all the other nodes, would allow revision to the network to improve its applicability and reliability.

The model provides an initial example of a rational, coherent approach to interpretation of forensic toxicological results. The model does need development, particularly in relation to exploring and accommodating any dependency between analytical results. Further research and collection of data for combinations of analytical tests would be very helpful in this respect. So to would be contributions from practitioners to help develop the nodes and relationships in the network. As with all Bayesian Networks, the model allows the scientist to explore the sensitivity of the network to varying assignments of probability values and thereby help test and develop the model.

Our aim with the current work has been to help move interpretation from a largely subjective, generalist approach to a more objective, case-specific, logical methodology utilising available relevant data and accommodating the inevitable uncertainties within a case.

Conclusions

1) Based on the network presented, the analyses of femoral blood, urine and vitreous for alcohol and urine for 5HTOL and 5HIAA (to establish the 5HTOL:5HIAA ratio) provide the best probative value to assist in the consideration of whether the individual had consumed ethanol and if they were above statutory limits at the time of the air crash.
2) VOC and witness evidence, thought conventionally to be useful, do not have as much influence on the issues of importance to the fact finder as the other analytical results.
3) More data needs to be collected to provide more robust, more reliable data to help assign probabilities of several of the nodes but, in particular, the 5-HTOL:5-HIAA ratio.

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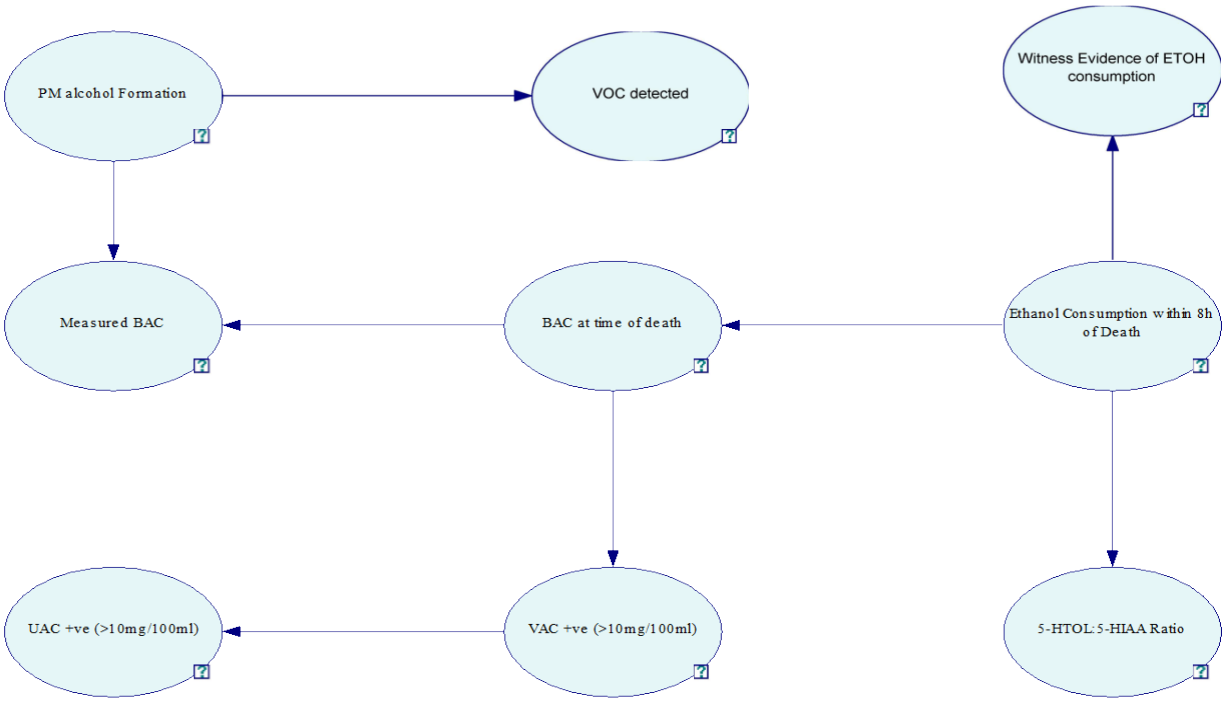


Figure 1. Bayesian Network for the inference from blood alcohol concentration in cases of aircraft crashes

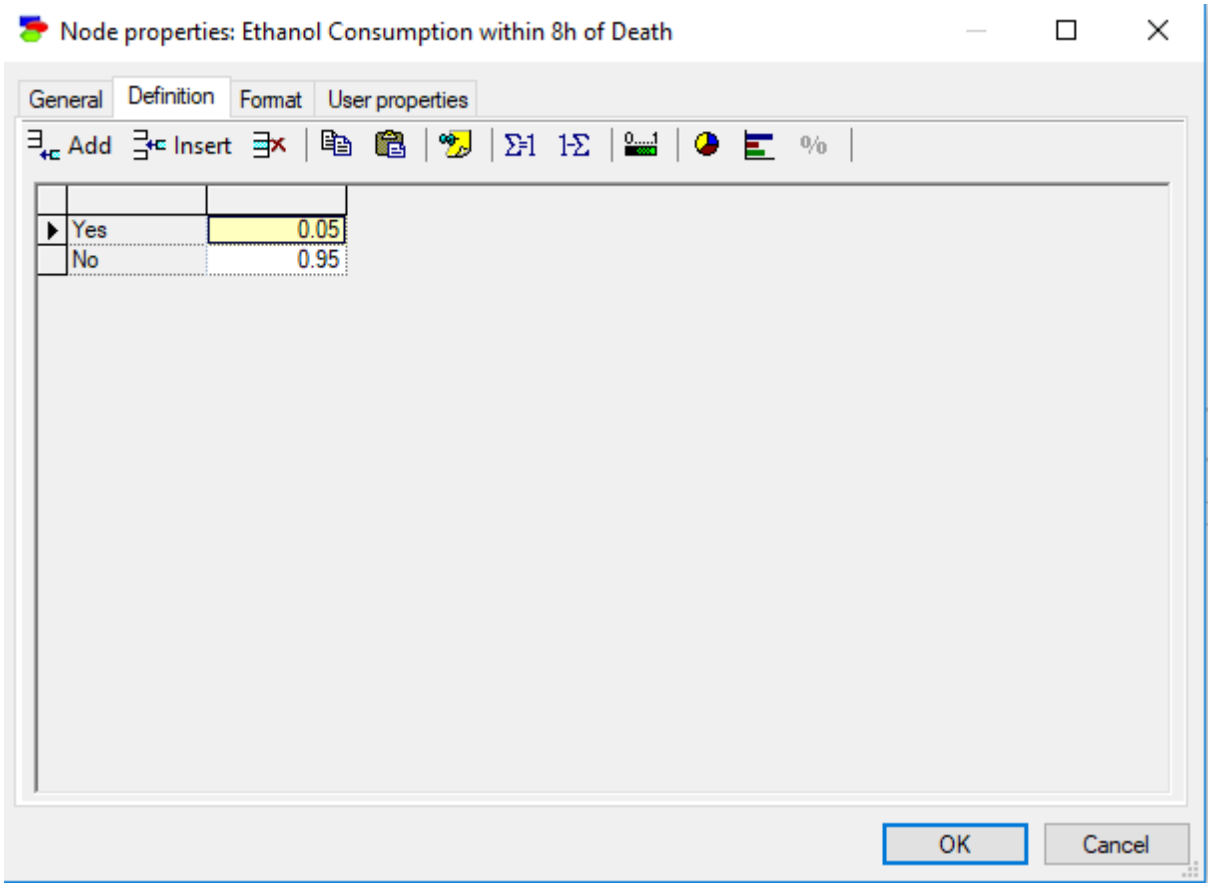


Figure 2: Probability Table for node 6. Ethanol consumption within 8h of death.

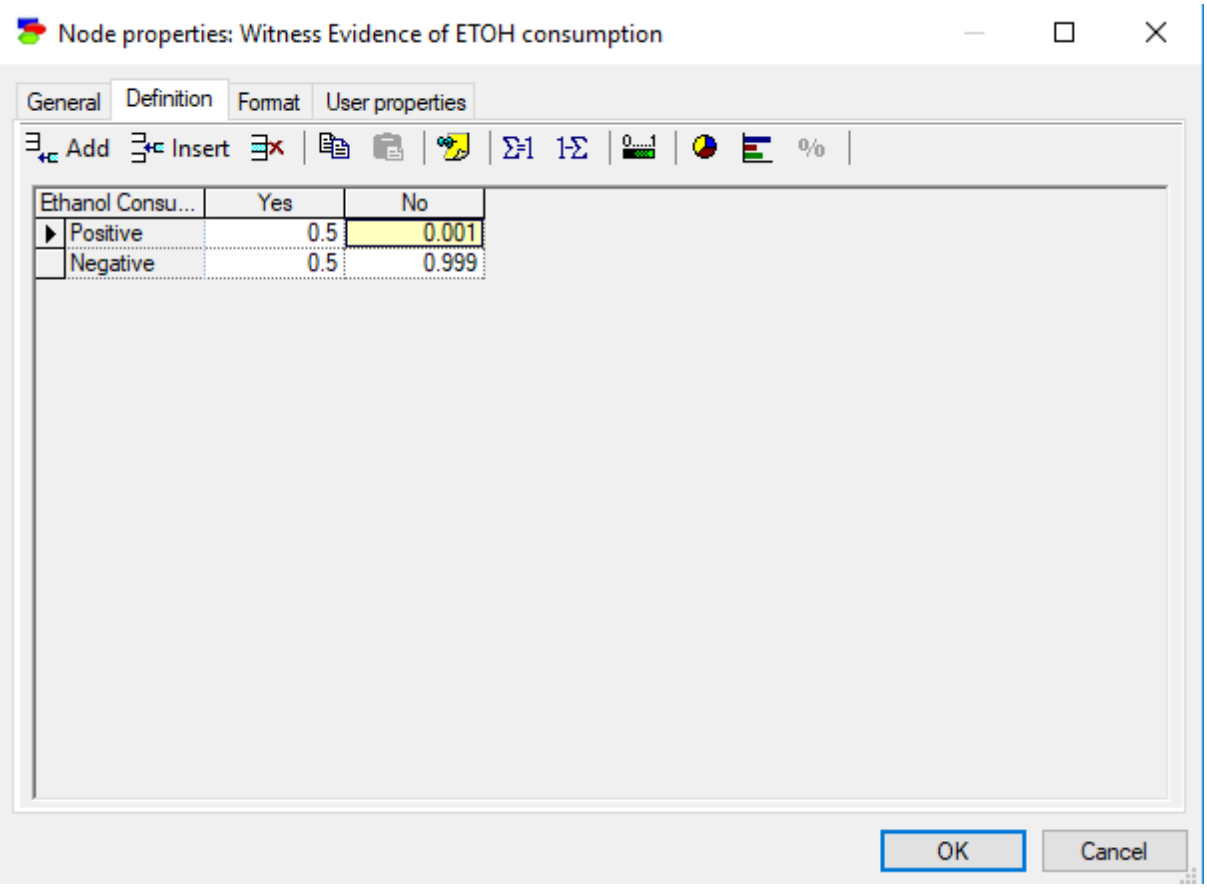


Figure 3 Probability table for node 3: Witness evidence of ethanol consumption

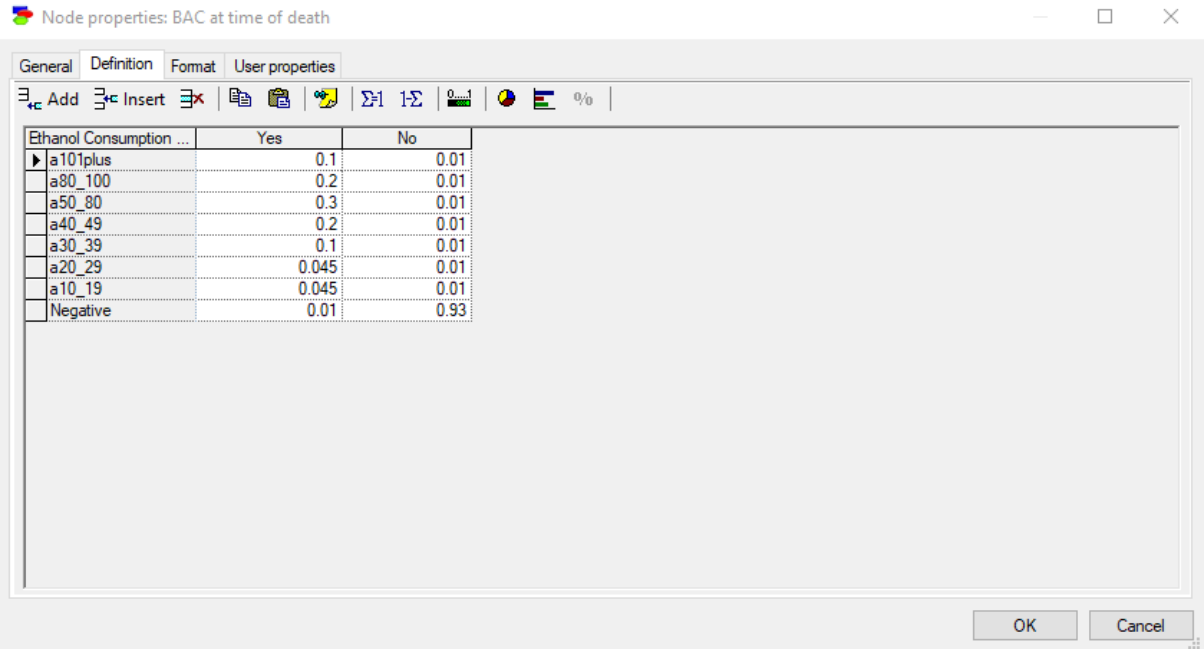


Figure 4: Probability table for node 5. Blood alcohol concentration at the time of death

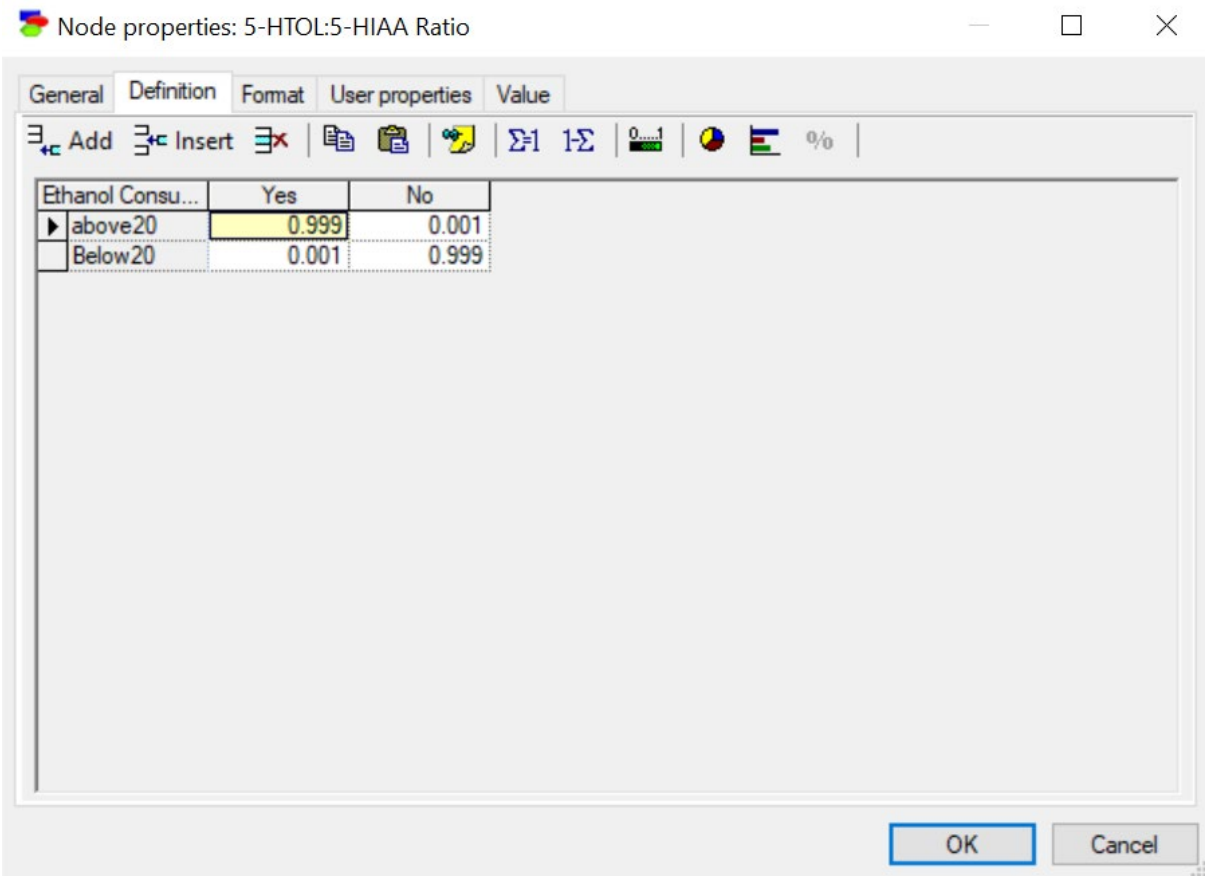


Figure 5: Probability table for node 9. The measured urine 5-HTOL/5-HIAA ratio

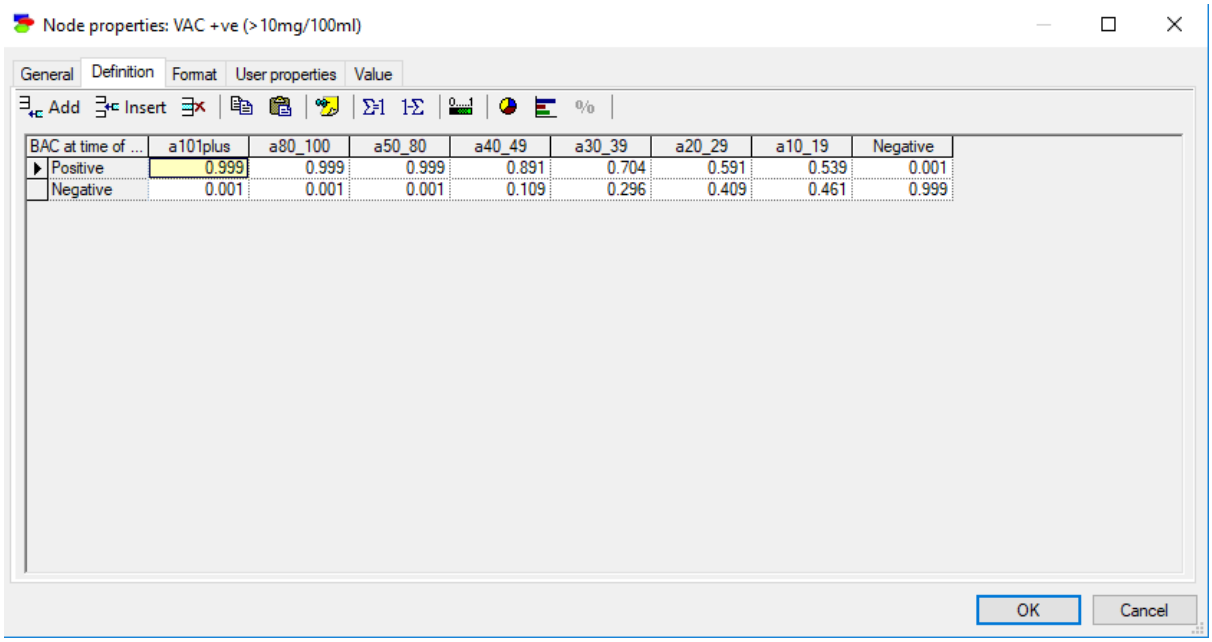


Figure 6: The probability table for node 8. Is vitreous humour positive for ethanol (ethanol >10 mg/100ml)

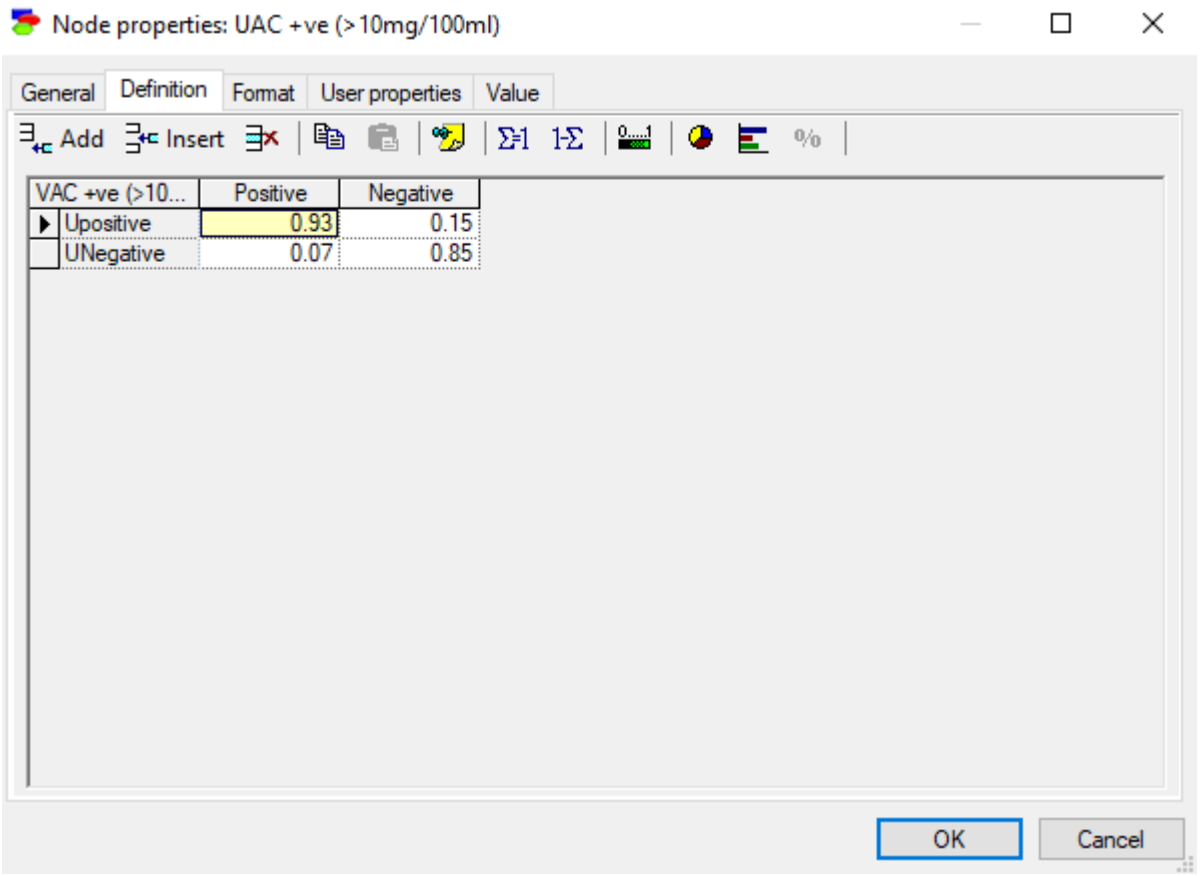


Figure 7: The probability table for node 7. Is urine positive for ethanol (ethanol >10 mg/100ml)

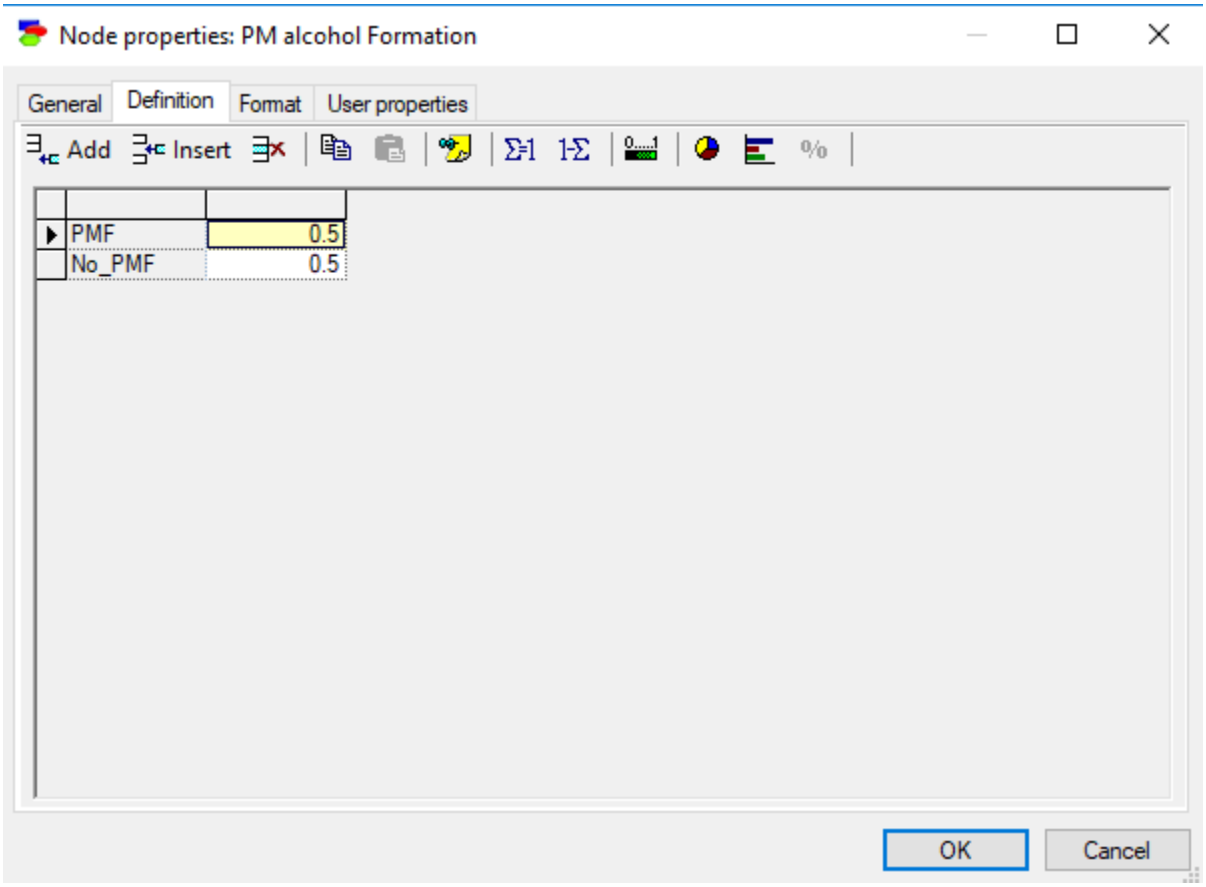


Figure 8: The probability table for node 1. What is the probability of postmortem ethanol formation.

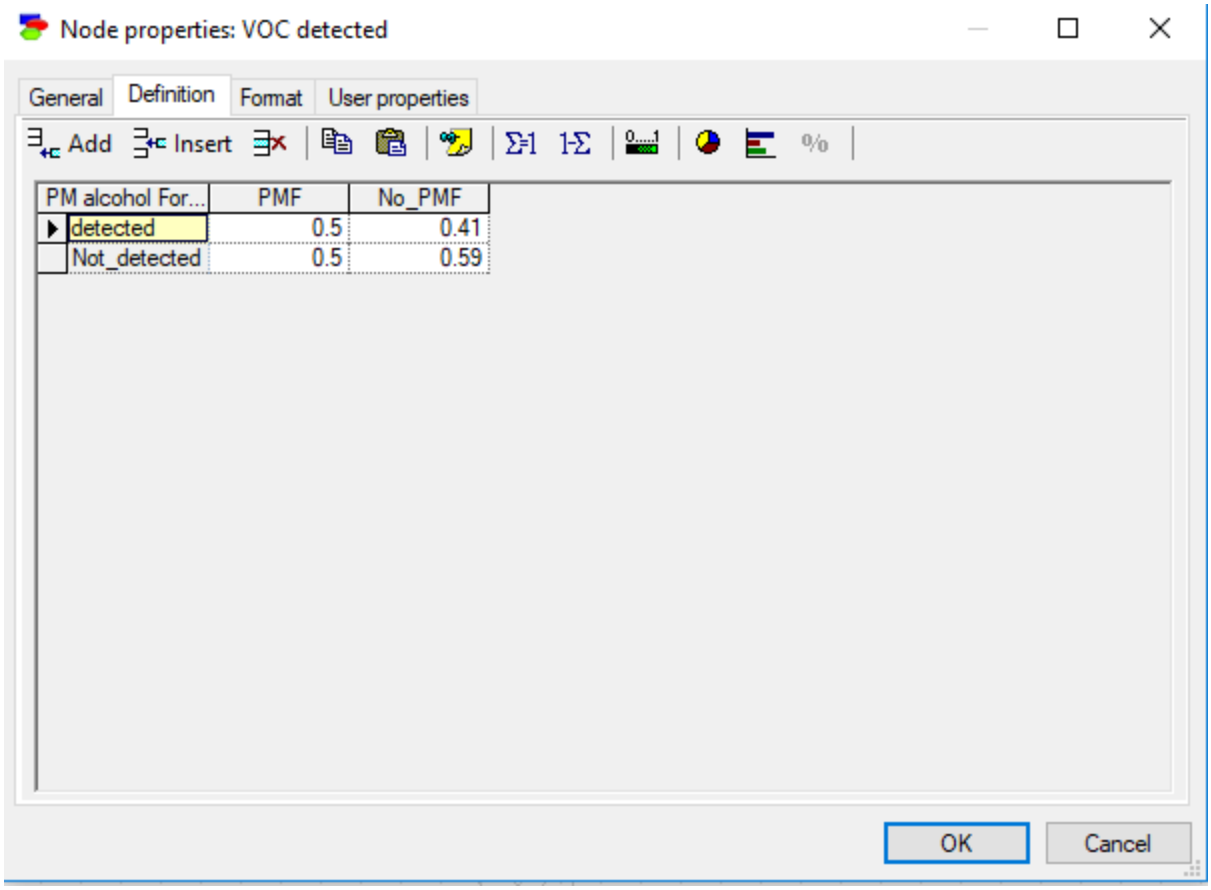
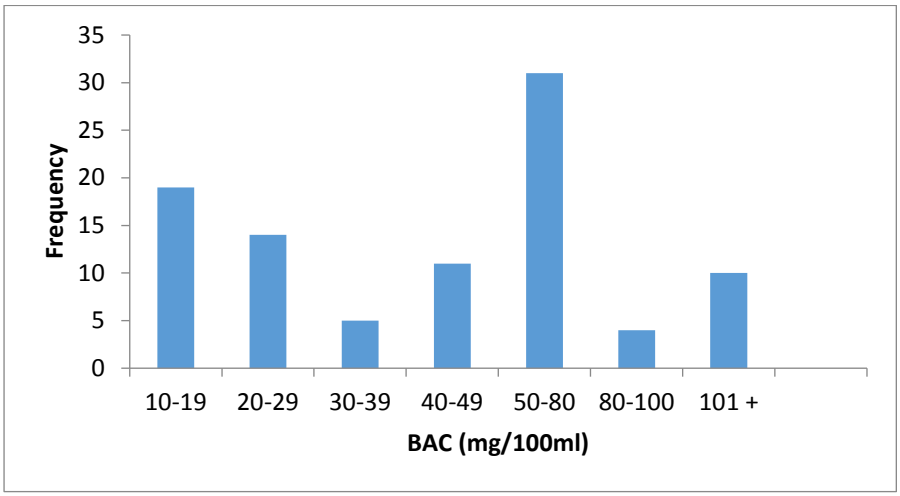
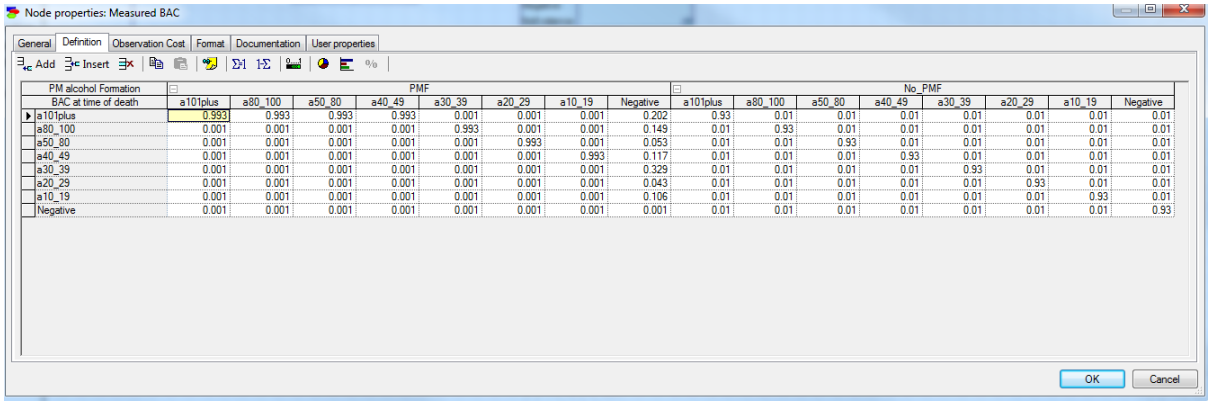


Figure 9: The probability table for node 2. Have volatile organic compounds (VOC) been detected in the analysed samples.

Figure 10: The probability distribution of blood alcohol concentrations in deceased individuals that had not consumed alcohol prior to death. Data used for node 4. The data was compiled from Mayes *et al*[27], Gillan & Bost [28] **and Zumwalt *et al*[29]**





PM alcohol Formation	PMF								No_PMF							
BAC at time of death	a101plus	a80_100	a50_80	a40_49	a30_39	a20_29	a10_19	Negative	a101plus	a80_100	a50_80	a40_49	a30_39	a20_29	a10_19	Negative
a101plus	0.993	0.993	0.993	0.993	0.001	0.001	0.001	0.202	0.93	0.01	0.01	0.01	0.01	0.01	0.01	0.01
a80_100	0.001	0.001	0.001	0.001	0.993	0.001	0.001	0.149	0.01	0.93	0.01	0.01	0.01	0.01	0.01	0.01
a50_80	0.001	0.001	0.001	0.001	0.001	0.993	0.001	0.053	0.01	0.01	0.93	0.01	0.01	0.01	0.01	0.01
a40_49	0.001	0.001	0.001	0.001	0.001	0.001	0.993	0.117	0.01	0.01	0.01	0.93	0.01	0.01	0.01	0.01
a30_39	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.329	0.01	0.01	0.01	0.01	0.93	0.01	0.01	0.01
a20_29	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.043	0.01	0.01	0.01	0.01	0.01	0.93	0.01	0.01
a10_19	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.106	0.01	0.01	0.01	0.01	0.01	0.01	0.93	0.01
Negative	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.93

Figure 11: Probability table for node 4: The analytically determined postmortem blood alcohol concentration of the pilot.

Figure 12: The states of the various nodes with no evidence. The width of the arrows indicate the strength of the evidence provided by the child node to the parent node, the width of the arrow being determined by the magnitude of the likelihood ratios within the child node.

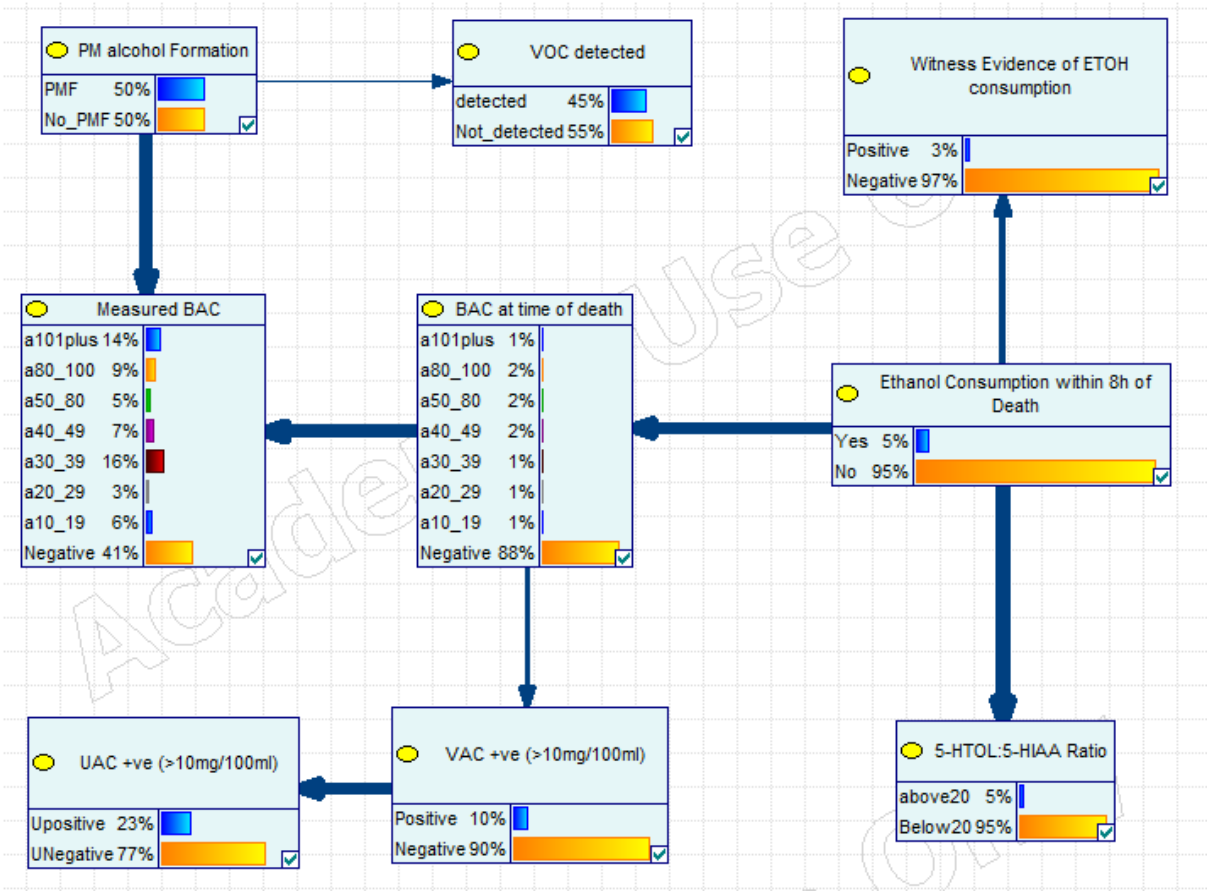


Figure 13 State of the various nodes based on the evidence for case 1 from Johnson *et al* [30]

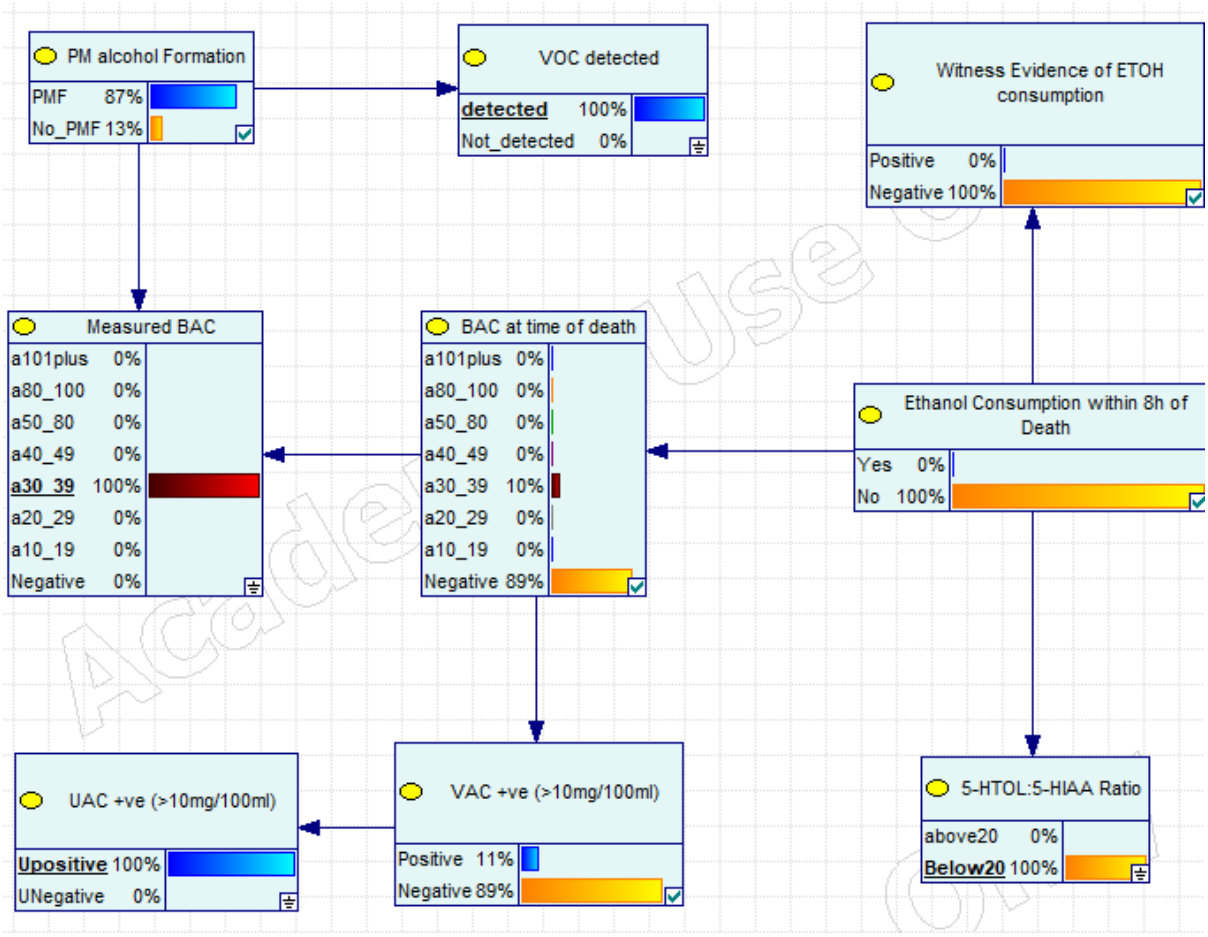


Figure 14 State of the various nodes based on the evidence for case 2 from Johnson *et al* [30]

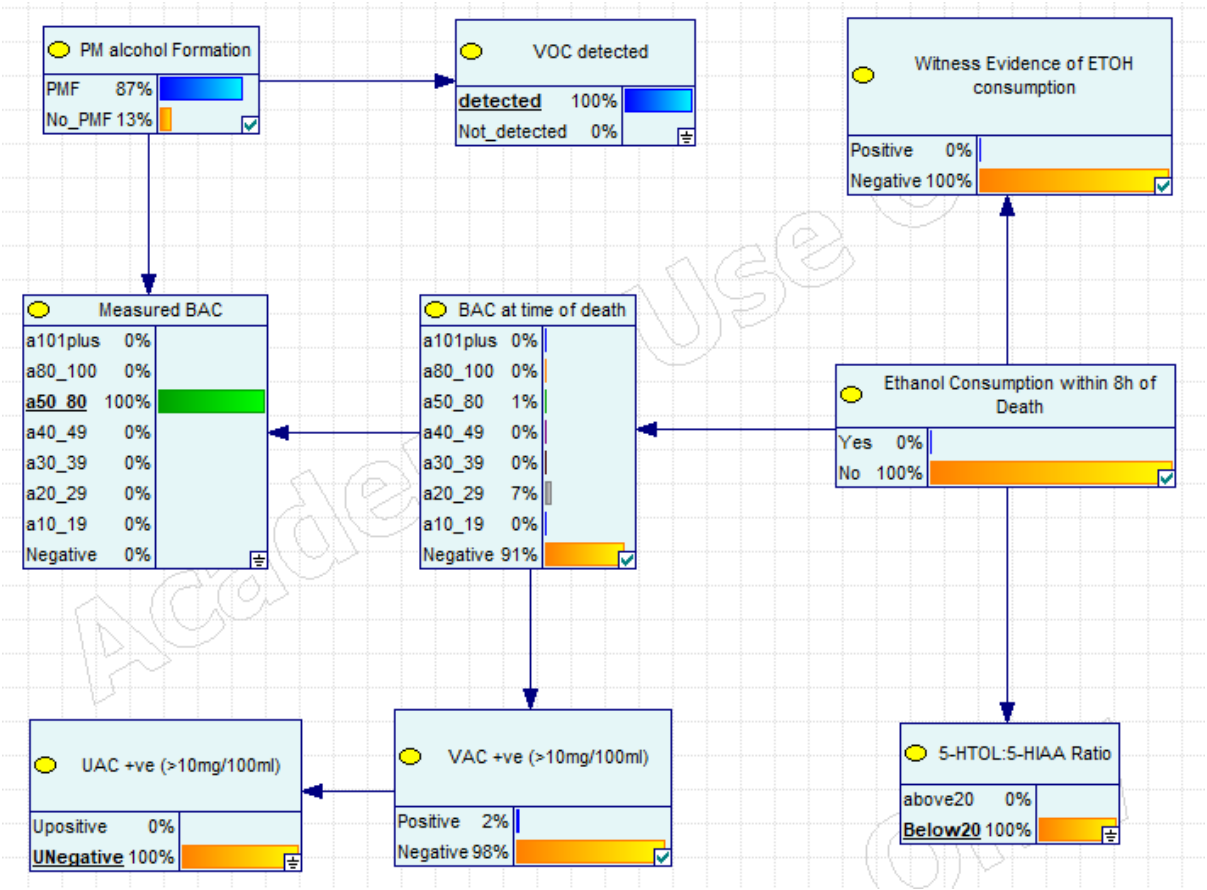


Figure 15 State of the various nodes based on the evidence for case 3 from Johnson *et al* [30]

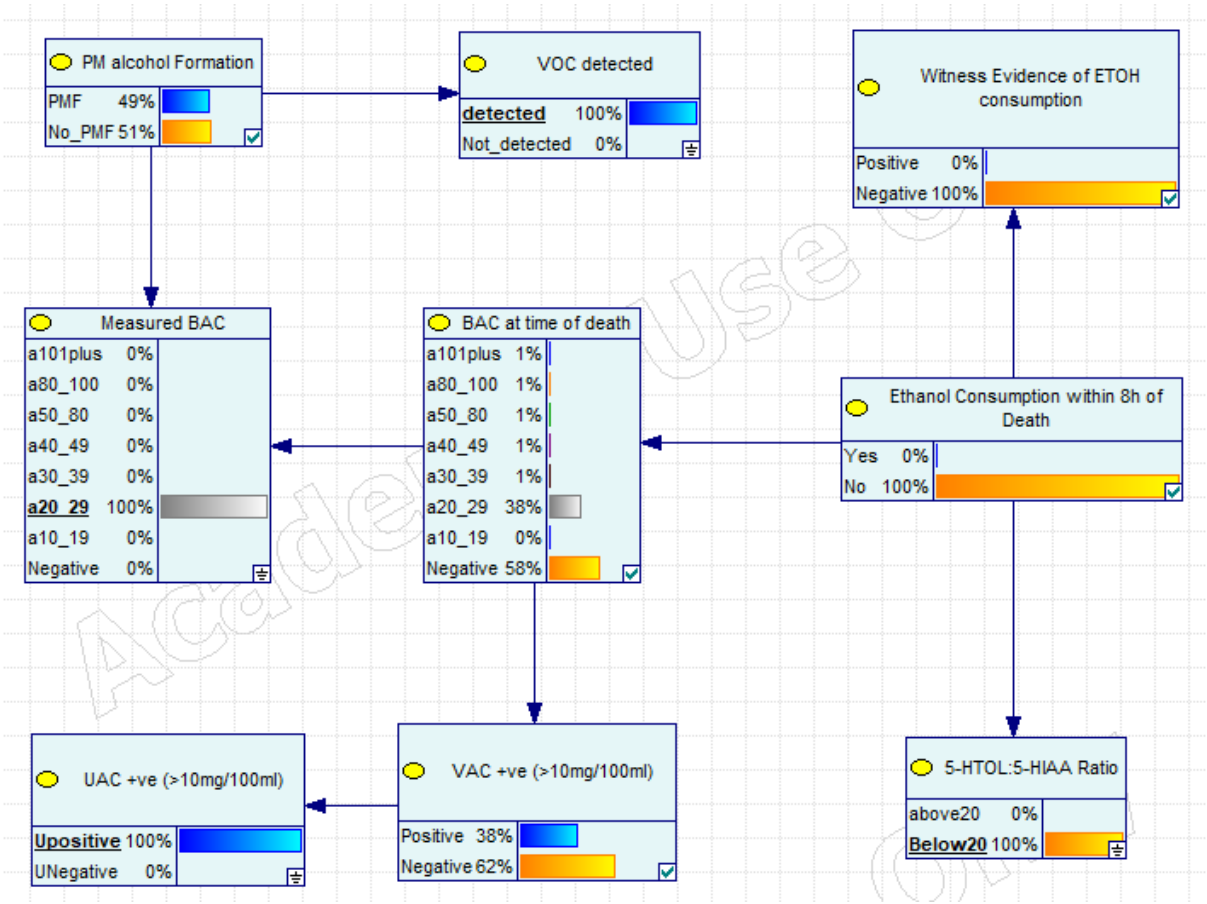


Figure 16 State of the various nodes based on the evidence for case 4 from Johnson *et al* [30]

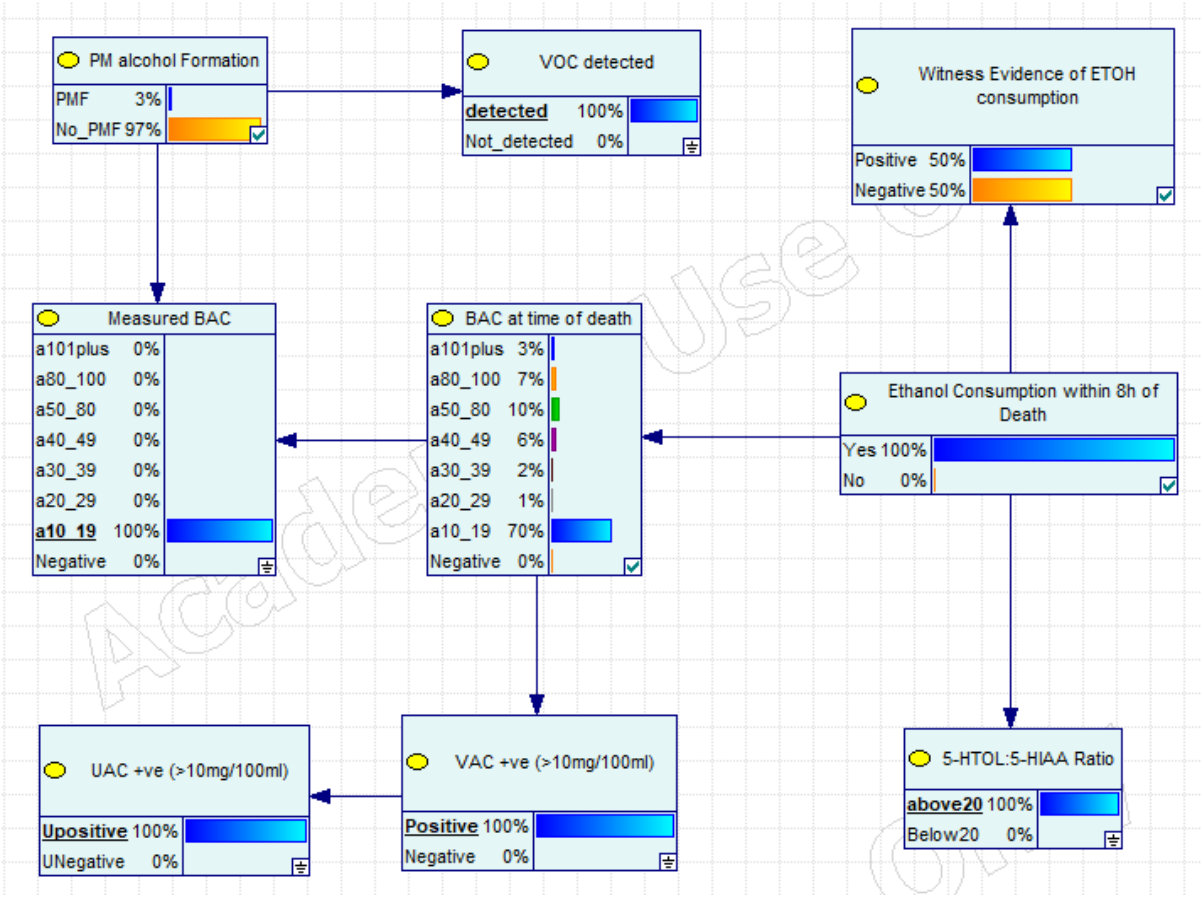
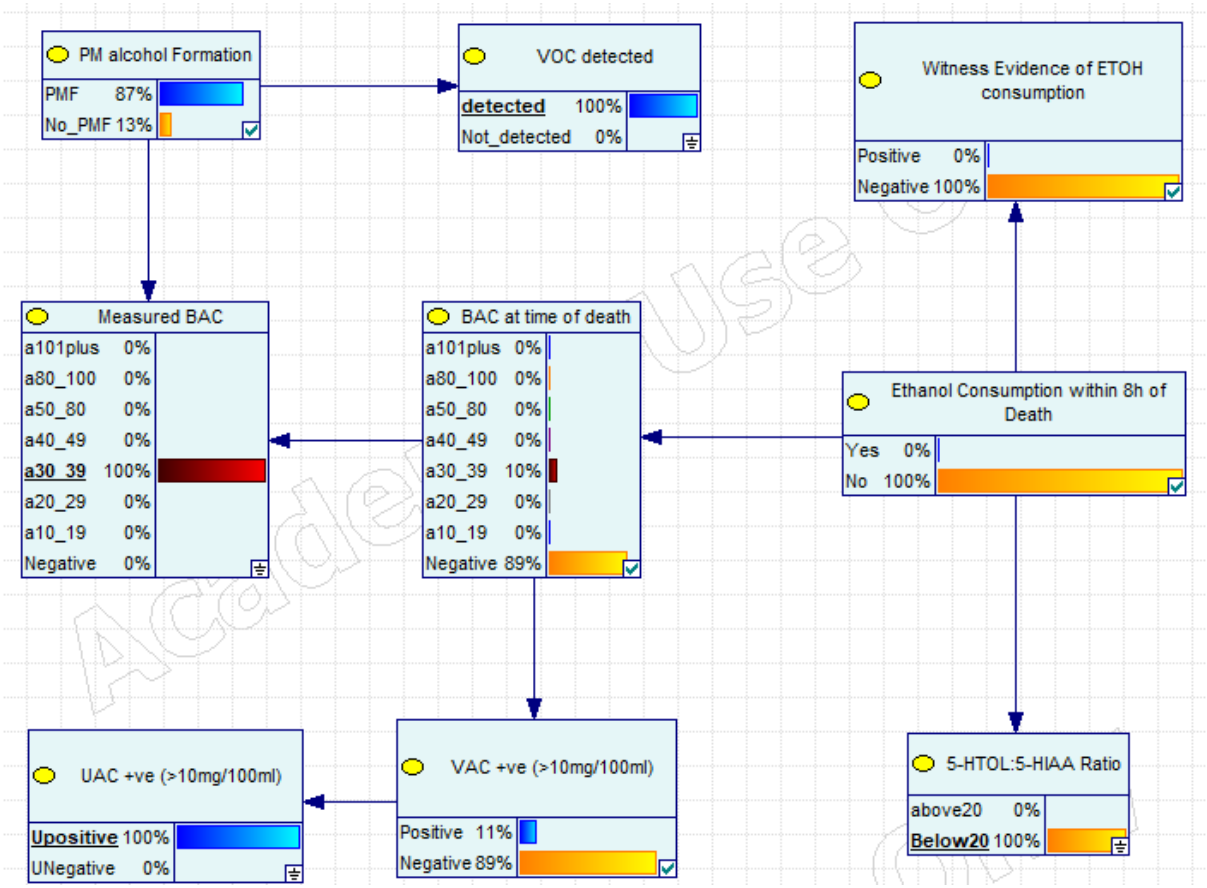


Figure 17 State of the various nodes based on the evidence for case 5 from Johnson *et al* [30]



Case	Blood mg/100ml	Urine mg/100ml	Vitreous mg/100ml	VOC's	5HTOL/5HIAA ratio (pmol/nmol)	Interpretation of result from Johnson *et al.*	Probability from Node 5 (BAC at TOD)	Probability from Node 6 (EtOH consumption within 8h of death)
1	38	25	-	+ve	2.1	PMF	Neg – 89%	No – 100%
2	54	9	-	+ve	3.2	PMF	Neg – 91%	No – 100%
3	22	18	-	+ve	0.41	PMF	Neg – 58%	No – 100%
4	17	25	25	+ve	67	No PMF	1—19 mg/100ml – 70%	Yes – 100%
5	31	48	-	+ve	0.08	PMF	Neg – 89%	No – 100%

Table 1: Comparison of the published aircraft accident interpretations from Johnson et al. [30] to probability outputs from the Bayesian network