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# Application of Bayesian methods and networks to ignition hazard event prediction in nuclear waste decommissioning operations

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ABSTRACT

The major purpose of the study is to examine how Bayesian networks can be used to represent and understand potential ignition scenarios in nuclear waste decommissioning. This is illustrated using a network to represent a situation with stacked storage boxes containing pyrophoric material removed from waste storage silos. Corrosion of this material during storage produces hydrogen which is released through a filter medium into the gap between the boxes. The probabilistic relationships used to indicate dependence between network nodes are expressed by conditional probability tables or C++ coded equations that relate to UK nuclear industry corrosion and storage data. The study focuses on optimal prediction of the likelihood of a flammable hydrogen atmosphere arising in the gap between stacked boxes and the conditions necessary to exceed the lower flammable limit. It is concluded that the approach offers a useful means of easily determining the manner in which varying the controlling parameters affects the possibility of an ignition event. The effect of data variation can be examined at first hand using the supplementary Bayesian Network that accompanies the article.

## 1. Introduction

Hydrogen explosion hazards have been a particular concern relating to waste storage decommissioning and reprocessing operations which involve Magnox containing waste (Kemsell et al., 2001). Corrosion of magnesium containing material in the waste sludge, together with the effects of radiolysis, produces hydrogen gas which can be held in pockets enveloped in the sludge. If these pockets are disturbed during processing or storage operations there is the possibility of developing a flammable atmosphere in the ullage space above the sludge. A useful discussion and survey of reactive metal corrosion during nuclear waste packaging has been provided by Serco Technical Consulting Services in an extensive report for the Nuclear Decommissioning Authority (NDA, 2018). Details of the corrosion and storage of Magnox-containing waste in the UK are also available from a report made available in the public domain by Nuclear Technologies plc (2018).

There are a variety of possible ignition sources that can develop during decommissioning, including electrostatic (Ingram et al., 2014) and mechanical (Jones et al., 2006; Averill et al., 2013; Averill et al., 2014a; Averill et al., 2014b; Averill et al., 2015a; Averill et al., 2015b). Of particular importance are those relating to surface heating or sparking caused by mechanical stimuli; e.g. sliding contact or impacts involving metal bodies or a metal body with a concrete silo wall. The presence of pyrophoric magnesium-containing material poses a much enhanced risk of an ignition source occurring. Averill et al. (2015a) have discussed the complex uncertainties involved in determining the ignition probabilities with pyrophoric surface substances present and suggested a mechanism for the ignition of hydrogen in air atmospheres by pyrophoric ($Mg/O_2$, $Mg/N_2$ or Mg/iron oxides thermite) reaction. It is also possible, at higher impact energy, for ignition of hydrogen in air atmospheres to occur with clean metal on metal impacts (Averill et al., 2014b).

Underpinned by a continuing body of research, the Hydrogen Hazards Unit at LSBU, has collaborated with Sellafield Ltd to produce a comprehensive Technical Guide to hydrogen safety.[1] This provides comprehensive information concerning the general design principles and calculations relating to hydrogen issues that could arise during nuclear decommissioning in the UK. An important component of the Guide is a road map approach to aid process engineers in recognizing the likelihood of an ignition event occurring. Following this work, the major purpose of this paper is to

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[1] I.ChemE Global Award 2015. Highly commended for outstanding achievement in process safety.

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examine how such road maps can be represented by corresponding Bayesian networks to better understand potential incident scenarios. Bayesian statistics also offers a means of including any prior knowledge that is available, particularly the relevant beliefs held by experts in the field. This is sharply different to classical statistical methods such as experimental design (Averill et al., 2013; Averill et al., 2014a) where prior information is discarded. Data that becomes available is used to continually update a Bayesian model or network which is initially specified by the prior knowledge.

Bayesian networks effectively mesh together Bayesian theorem probability calculations and graphical theory. They facilitate an immediate visualization of all dependent and independent relationships within the model enabling a wider understanding of the process. An important aspect of these networks is that the conditional probabilities used to represent the uncertainty of the true state of a variable can be changed, with the variable being set to a known value when relevant hard evidence is discovered or the uncertainty updated following new but still uncertain evidence. These changes result in an update of the unknown nodes in the network which involves the application of sophisticated algorithms to carry out complex probability calculus. In this manner, the effect of changing conditions can be seen propagating throughout even highly complicated networks. Backwards analysis through the network occurs as well as forward analysis, thus enabling the full effect of available hard evidence to be easily visualised.

This paper focuses on optimal prediction of the likelihood of a flammable gas atmosphere arising in the gap between stacked waste storage boxes which contain pyrophoric material removed during nuclear decommissioning operations. The model is based on realistic data related to the corrosion and storage of Magnox-containing waste in the UK. Although it deals with a specific application, it is envisaged that a similar approach could easily be developed for other storage and possible ignition scenarios. A summary introduction to the relevant aspects of Bayesian inference and networks is given in the next section.

## 2. Bayesian conditional probability, likelihood and networks

In our laboratory ignition experiments (Jones et al., 2006; Averill et al., 2013; Averill et al., 2014a; Averill et al., 2014b; Averill et al., 2015a; Averill et al., 2015b), the probability of ignition was simply determined by the number of times it actually occurred divided by the total number of similar tests carried out. This is clearly useful to deal with situations which replicate the experimental conditions but may be of limited use in the real world where there is uncertainty and the possibility of enormous environmental variation. If there are no previous reported instances or experimental test results of ignitions occurring under the same conditions being considered, an inclusive approach can be adopted based on Bayesian or conditional probability: this can formalise a consensus belief under conditions of uncertainty and utilise all of the information available.

Although Bayes' theorem has in recent years been much discussed in the literature, there can be some difficulty in properly understanding the fundamentally important difference between likelihood and conditional probability. Bayes' theorem can be expressed as a relationship between the *prior* $P(\mu)$ and the *likelihood* $P(Y|\mu)$ (with a data term *P(Y)* included as a scaling or normalising parameter) to give an updated *posterior* $P(\mu|Y)$.

$$P(\mu|Y) = P(Y|\mu)P(\mu)/P(Y) \quad (1)$$

Here, the prior represents a probability distribution (hypothesis) of the possible mean value for the data being considered which allows for the incorporation of both pre-existing knowledge and expert belief. It is updated by the likelihood ratio $P(Y|\mu)/P(Y)$ which considers any future evidence and determines the probability of that data occurring for each possible value of $\mu$ within the distribution. Multiplying these probabilities by the prior distribution then allows the posterior to be obtained which represents the altered and updated probability distribution of the mean value. It should be recognised that likelihood values differ from conditional probability, in that they are not constrained to be mutually exclusive and exhaustive with a total probability value of unity: this makes it necessary for likelihood ratios to be used in the updating process rather than individual likelihoods. The application of likelihood ratios can be illustrated using a simple example involving ignition laboratory tests results. Fig. 1 shows the likelihoods (determined from a binomial distribution) for a series of 10, 20 and 30 tests in which there were 4 and 8 and 12 positive ignition results. The plots are scaled so that the best supported ignition probability of 0.4 for each set of tests corresponds in each case to a likelihood of 1. Clearly the increase in number of tests has narrowed down the likely range of the ignition probability: the likelihood of the ignition probability being 0.6 as apposed to 0.4, for example, is seen from the Plots as greatly decreasing with increase in the number of tests involved. This observation is formalised by comparing the likelihoods with

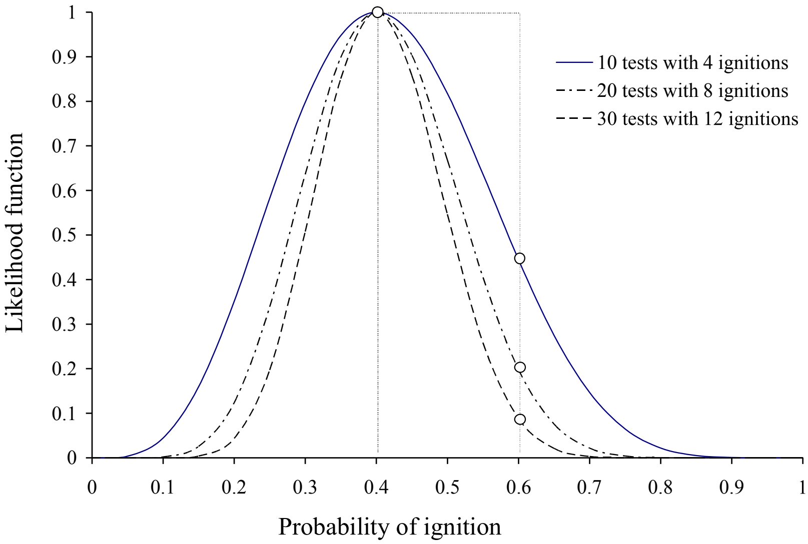

**Fig. 1.** Likelihood function for a series of ignition tests.