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Application of Bayesian Belief Network for the Analysis of Accident Data in the Bioenergy Manufacturing Sector

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This paper presents an analysis of the cause and effect relationships found in the safety analysis of bioenergy processes by employing a dynamic Bayesian Belief Network assessment over a period of 10 years in the United States. These networks are considered to be more descriptive to model the fundamental relationships in the safety analysis of process industries where diagnostics risk assessment tasks are being conducted. Combining Bayesian Belief Network assessment and statistical simulation provides a powerful tool for risk assessment. Agena Risk was used here as the software to execute/perform this risk assessment. The US accidental database in the bioenergy sector was constructed over a 10 years period for the input data. The analysis was divided between accidents that caused material damage and accidents resulting in injuries and fatalities. The real difference stands in the approach: here, the interdependence among different factors which interact and affect one another in building the accidental path. The Bayesian Belief Network method, supported by a customized tool, has been demonstrated to be flexible, transparent, and suitable for learning from the past and forecasting the future.
Keywords: Bayesian Belief Network, Integrated Biorefining, Risk Assessment

1. Introduction

Demand for energy fuel showed a marked increasing trend in the last decades, while reliance on fossil fuel such as coal is unsustainable for environmental reasons especially in sensitive areas (Vairo et al., 2014) and it is susceptible to economic and political vulnerabilities for non-producing Countries. The challenge in developing alternative developing alternative renewable energy resources that would accommodate the energy demand of the future is conditioned by the accurate consideration of all economic profitability and health, safety and environmental impacts. Economic issues can be faced according to the techno-economic sensitivity approach successfully applied in the assessment of palm—based biorefinery (Romero Perez et al. 2017). Additionally, in order to enhance the economic profitability of biofuel production, the energy efficiency of the processes must be optimized by maximizing heat recovery and minimizing energy degradation, e.g. by pinch and exergy analysis (Jia et al., 2017). The different phases of the bio-energy production process imply that hazardous materials are forged, processed and gathered, with the possibility of causing accidents resulting in economic, social, environmental and occupational losses (Jenkins et al., 2013). Accident evolving scenario are clearly connected to the inherent hazards of bio fuels, in some instances (e.g. thermal radiation from ethanol pool fire) exerting an impact even more severe than conventional ones (Palazzi et al., 2017). As amply reported, the in-depth technical analysis of case histories can improve our understanding of the hazards related to novel and consolidated processes or activities, forcing operators to take appropriate risk preventive and mitigating measures (Vairo et al., 2017).Taking into account that the concept of risk analysis is intimately linked with the idea of uncertainty, statistical analysis appears to be an instrument of primary relevance for the optimal choice of the strategy. This research work is deeply coupled with the previous one done by (Seay et al., 2017) for the statistical study of accident data for bioenergy sector based on second generation feedstocks, where it was evidenced that a non-negligible risk profile may be attributed to bio-energy industries. In the current study, the analysis is performed by a different approach based on the Bayesian theory concretized by AgenaRisk tool. In fact, in the area of process safety, it was recently evidenced how applying experience and historical data with Bayesian network coupled with conventional

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HazOp can help in addressing issues related to operational risk management (Cameron et al., 2017). This section would like to be a means more than an end, to introduce and explain this technique and its potential. Bayesian approach is the theory used to examine the uncertainty of probability model parameters and is recognized as a proper way to make use of experts' opinions and subjective information (Ding et al., 2012). The crux of the Bayesian approach is to build on existing data and to absorb new knowledge to lower uncertainty, as well as to improve understanding of complex systems possibly in combination with well-established techniques such as HazOp (Pasman et al., 2016).

2. Materials and methods

This section is going to introduce the tools used for the analysis. The analysis will focus on US accidental data over a 10 years period for bioenergy sector and will be divided between accidents that caused just material damage and mishaps, which caused injuries and fatalities. The gathered information from different US databases and sources comprises of general data, including activity, location, scenario, causes, injuries and fatalities. The foundations of Bayesian theory and the AgenaRisk tool are herein given to introduce the potential of the method.

2.1 The Bayesian theory and risk analysis

A Bayesian Belief Network (BBN) is a sort of statistical model; specifically, it is a probabilistic graphical model which represents a set of random variables with their mutual dependencies via Directed Acyclic Graph (DAG). A DAG is a direct graph with no directed cycles: vertices and edges are present, but as illustrated in Figure 1 (a). There is no way to start out any vertex and to follow a directed sequence of edges that eventually loops back to the same vertex again. BBN are type of DAGs in which nodes represent stochastic variables; specifically, they may consist in observable quantities, latent (inferred variables), unknown parameters or hypothesis. This research explores the outcome of coupling Bayesian theory within risk analysis in practice. Bayes theory explains how to update a probability distribution of values of a parameter. By applying the theorem to a failure rate λ, means considering it as a random variable expressed in the form of a probability density function, rather than a single value variable (Pasman et al., 2011).

$$f(\lambda/E) = \frac{L(E/\lambda)\, f(\lambda)}{\int_0^\infty L(E/\lambda)\, f(\lambda)\, d\lambda} \qquad (1)$$

where f (λ) is the distribution of failure rate values, while L(E/λ) represents the likelihood function (the probability that event E is observed given λ is true). Note that the denominator is useful to normalize the result between 0 and 1. A previously hinted, Bayesian Belief Nets (BBNs), belong to the family of DAGs, such as fault trees, event trees, bow ties, etc. Because of their capability in making inferences and diagnoses, they are considered attractive tools to organize knowledge (Pasman et al., 2011). The nodes of the structure are usually drawn as ellipses and are connected through arcs. These last ones describe the relationships, while the nodes contain probability information, as well as operations between functions. As in a family, there are parents and children: the former are represented by starter nodes, while the latter are the nodes further down the structure, as illustrated in Figure 1 (b). Taking account that risk analysis consists in various steps (risk identification; risk estimation; risk control and management), it is important not to forget the concept of uncertainty that accompanies all the steps.

The Bayesian approach can be viewed as an instrument capable of examining the uncertainty of probability model parameters, its application in risk analysis has three components (Ding et al., 2012):

- Build decision framework, take control of the decision process, provide a program for inference and decision.
- Estimate the distribution of risk, which is the main part of risk analysis.
- Parameterize the model.

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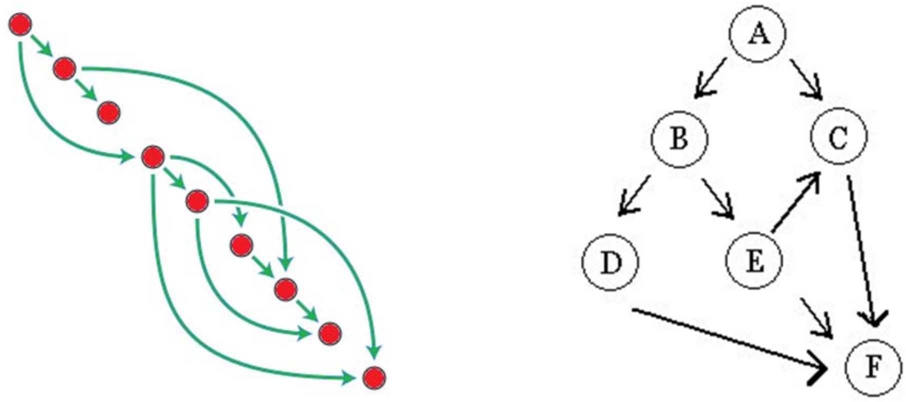


(a) *(b)*

Figure 1: (a) Representation of a Directed Acyclic Graph (b): Representation of a Bayesian Network.

2.2 An approach based on AgenaRisk

The paper relies on a customized approach developed starting form AgenaRisk, a visual, intuitive and powerful tool for modelling risk and for making predictions about uncertain events. It combines the benefits of BBN, statistical simulation and spreadsheet-like analysis. It can be applied to a variety of problems which involve uncertainty, and it is projected to model problems using risk maps, which are a combination of statistical simulation and BBN technologies.

Taking account of the statistical analysis performed by Seay et al. (2016), the network analyzes the happening of an incident or accidental risk, as well as consequence probabilities and its associated impact on environment and society. The whole network can be considered as a propagation of likelihood of given chains of adverse events and requires considerable amounts of data. Thus, computational complexity will grow exponentially as the number of parents will increase. The sensitivity analysis task has to be underlined as a key which helps to determine the most influential node of the network. Figure 2 shows the AgenaRisk Result as a risk map for modelling causal relationships of electrical failure. Note that Boolean nodes are used for probability calculation with a default status True or False. If parent value is greater than 0.5, it will be True, otherwise, it will be considered False. Probability tables allow to quantify the mentioned relationships by using explicit probability values or their expressions. Highly configurable risk graphs can be generated through the model; finally, sensitivity analysis is able to detect high-impact variables. Node Probability Tables (NPT) are fundamental components of the worked out model; probability information are recorded in these tools, and they represent the structural relationship of the model itself. For a node with no parents, the node probability table is simple, while it becomes more complicated in case of nodes with parents, for they contain conditional probabilities. The probabilities may depend on historical data or by experts' opinions. Boolean, statistical, mathematical expressions, as well as table partitioning, are used in the model. Note that when the sample run is over, risk map squares indicate risk events relevant to each respective cause; arrows between them represent the existent interdependence. Key findings responding to each run, are shown in the boxes at the end of each map; risk likelihood shown in the squares, represent the probability of events contributing to the results.

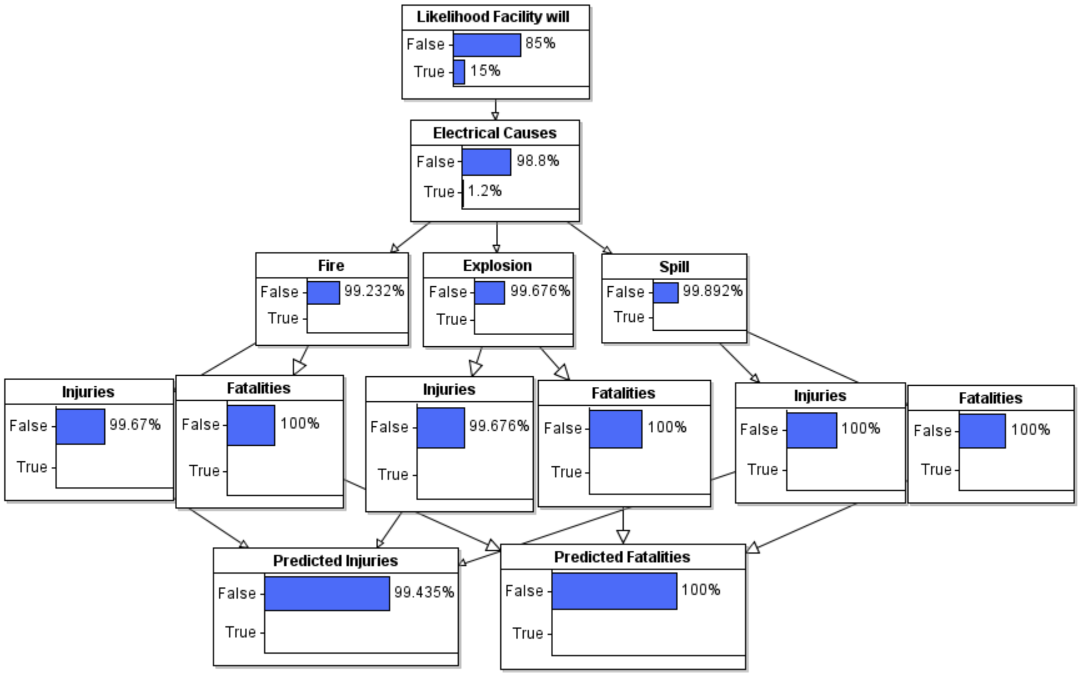


Figure 2: Risk Map modelling for Electrical Failures

3. Results and discussion

Six causes of accidents were studied for the purpose of this analysis: electrical failure, mechanical failure, natural events, process chemistry failure, under-investigation accidents and unknown failure reasons. All of these causes led to severe catastrophic consequences, including financial losses, injuries and fatalities. For risk modelling with AgenaRisk, just injuries and fatalities were taken into account in this research. Figure 2 presents the risk map associated with the probability of an accident caused by electrical failure in integrated bio-refineries (IBR), as well as the consequence occurrence anticipation in the bottom tier.

Probability values are True = 0.08 (8% chances of electrical failure contributing towards an accident, by input data), and False = 0.92 (92%). As the map is back propagated, it can be noticed that injuries and fatalities are dependent upon the risks in the form of fire, explosion and spill; these ones, also can be propagated back to their parent node, which is electrical failure. From this map, a risk path can be drawn, showing the maximum risk node and the minimum risk node and forming a causal risk relationship, as risks are interdependent on each other. Risk map shows that there is a low probability that an electrical failure event may occur (1.2%). Key findings of the model are likelihoods of injuries and fatalities which are, approximately, 0.05% and 0.00% .Note that likelihood of fatalities is zero, because no fatality has been recorded in this sector, according to input data. Figure 3 shows the probability and the consequences of accidents in IBRs because of mechanical failure. Probability values calculated from the database correspond to 20% chances of mechanical failure by input data. After the run, it can be observed that the probability of occurrence of mechanical failure is very low, equal to 3%. Its consequences are represented by key findings in form of likelihood of injuries and fatalities, which are approximately 0.15% and 0.00% (any fatality recorded, according to input data). Figure 4 (a) represents the likelihood of accidents and the resulting consequences coming from natural events. Probability values are True = 0.03 (3% chances of natural events, by input data), and False = 0.97 (97%). As expected, the probability of occurrence of natural events after model run is recorded very low, even compared with electrical and mechanical failures, equal to 0.45%. Its consequences are represented in form of likelihood of injuries and fatalities, which are approximately in total 0.12%. Concerning accidents due to process chemistry failure, likelihood of happened events is shown in Figure 4 (b).

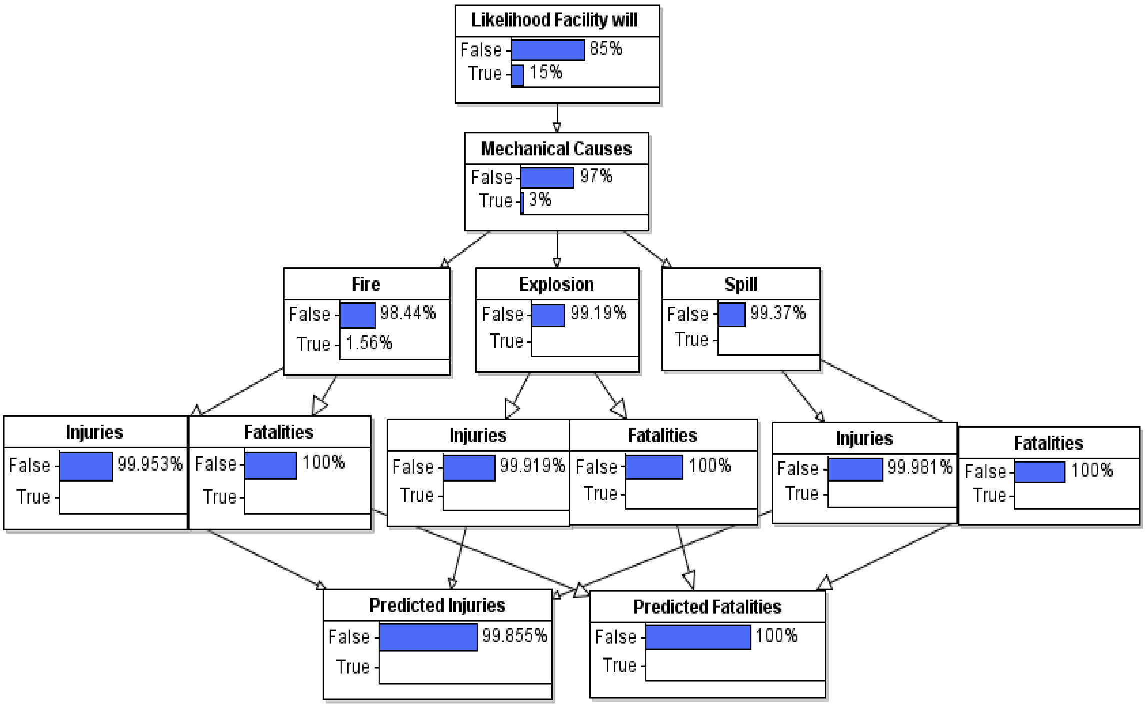
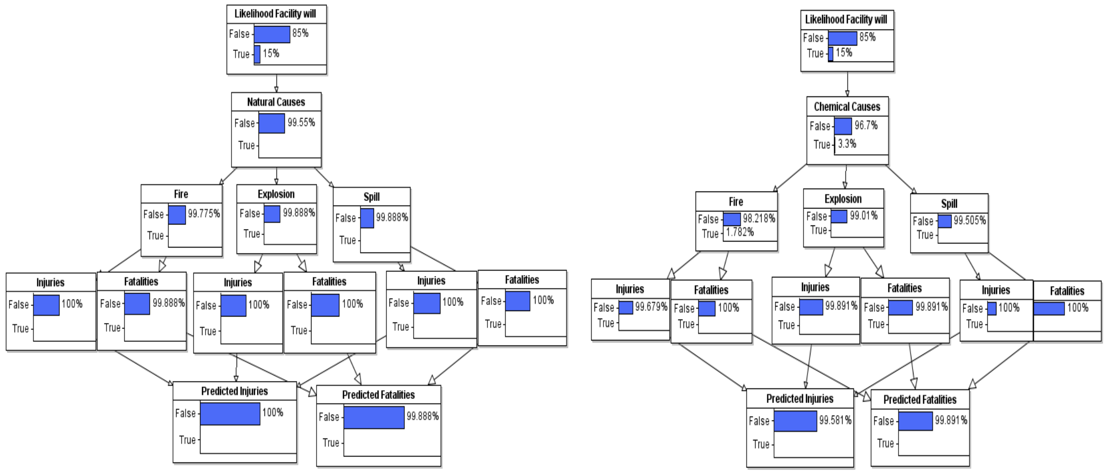


Figure 3: Risk Map modelling for Mechanical Failures.

Probability values are: True = 0.2 (22% chances of process chemistry failure, by input data) and False = 0.78 (78%). Probability of occurrence of events because of process chemistry failure after model run, is recorded 3.3%, which is higher than the previous three failure causes (electrical, mechanical and natural). Likelihood of consequences (injuries and fatalities) are approximately 0.42% and 0.10%. Figures 5 (a) and (b) show the probability and consequences of accidents in IBRs because of under-investigation accidents and unknown failures. Probability values for NPT are: True = 0.07; 0.40 (7% under investigation; 40% unknown reasons) and False = 0.93; 0.60 (93% and 60%), respectively. Probability of occurrence of these events are recorded as 1.05% and 6%. The consequences are represented by key findings in form of likelihood, approximately 0.46%; 1.1% for injuries and 0.10%; 0.29% for fatalities, respectively. A detailed risk map of whole network is also created by combining all the probabilities, which shows the probability of accidents because of all failures herein described. Key findings of this detailed work is enclosed in two squares, represented by the overall predicted injuries and fatalities. All failure causes are combined in the network, and the node probability data is the same used for individual runs. Individual consequences are so combined into one final injury and fatality tier. In this final run it is assumed that all the above information is true. The detailed risk map shows low probability of these events happening, and the combined key finding of the model is the likelihood of overall predicted injuries and fatalities, which is approximately 2.51% and 0.60%. Although these values represent a low probability of occurrence, the chance for them to cause damage in terms of injuries and fatalities, is a question that has not to be underestimated.

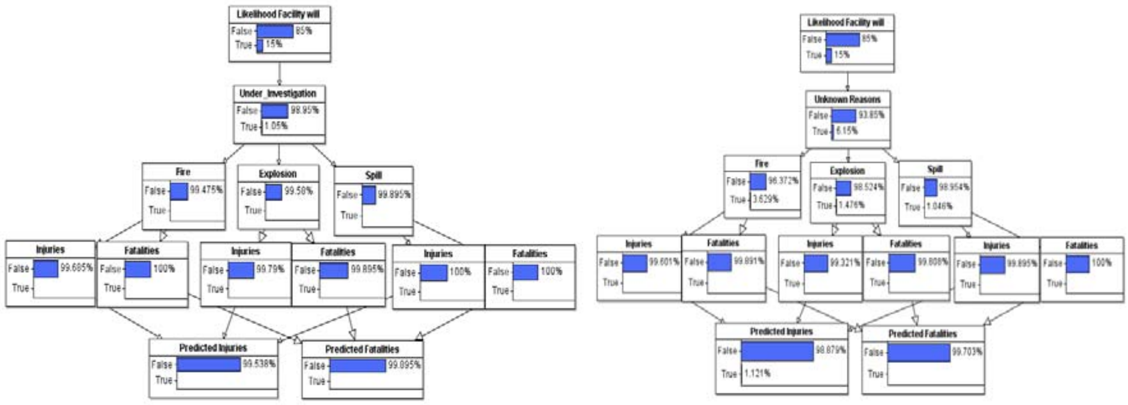
4. Conclusions

Results obtained through this method are not far from the ones obtained by the previous work reported in the scientific literature. The real difference stands in the approach: here, the interdependence among different factors which interact and affect one another in building the accidental path is exalted. The BBN, supported by the customized tool demonstrated to be flexible, transparent, suitable for learning from the past and forecasting the future. Fast methods such as LOPA, can be coupled with the results of this section to make possible the risk assessment of a specific case study, with reference to MAH provoking injuries and fatalities; BBN analysis on accidents which implied just financial losses, on the other hand, can be the basis of construction for an economic sustainability study of 2nd generation biorefineries. Both aspects will be treated in the future work.



(a) (b)

Figure 4: Risk Map modelling (a) Natural Events, (b) Process Chemistry Failures.



(a) (b)

Figure 5: Risk Map modelling, (a) Under Investigation Failures, (b) unknown Failures.

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