Applications of Bayesian networks in Chemical and Process Industries: A review

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Despite technological advancements, chemical and process industries are still prone to accidents due to their complexity and hazardous installations. These accidents lead to significant losses that represent economic losses and most importantly human losses. Risk management is one of the appropriate tools to guarantee the safe operations of these plants. Risk analysis is an important part of risk management, it consists of different methods such as Fault tree, Bow-tie, and Bayesian network. The latter has been widely applied for risk analysis purposes due to its flexible and dynamic structure. Bayesian networks approaches have shown a significant increase in their application as shown by in the publication in this field.
This paper summarizes the result of a literature review performed on Bayesian network approaches adopted to conduct risk assessments, safety and risk analyses. Different application domains are analysed (i.e. accident modelling, maintenance area, fault diagnosis) in chemical and process industries from the year 2006 to 2018. Furthermore, the advantages of different types of Bayesian networks are presented.

Keywords: Bayesian networks, Dynamic Bayesian Networks, Object-Oriented Bayesian networks, Chemical industry, process industry, risk analysis.

1. Introduction

After the middle of the 20th century, chemical industries witnessed a huge development from all sides. This development is just a reflection of human needs. We can find different kind of industries that are classified as chemical plants including; oil and gas industry, the pharmaceutical industry, and manufacturing industry (Reniers (2010)). Not only the plants that deal with products in high pressure and/or temperature are considered, but also, industries that store or transport hazardous materials are included. The need for methods that facilitate the modelling of these plants and deal with their complexity is fundamental. Also, the aforementioned methods shall help decision makers to take appropriate actions and decisions to guaranty the safety within chemical industries. Different methods have been proposed in the last sixteen years, among them; Hazard Operability analysis (HAZOP), Failure Modes, Effects and Criticality Analysis (FMECA), Fault tree analysis (FTA), and Event tree analysis (ETA). These methods have become more challenging and time-consuming particularly after the development and the complexity of todays process industries. The need for techniques to overcome the limitations of the before mentioned methods is crucial. To this end, researchers have adopted probabilistic graphical models like Bayesian Networks (BN) for reliability, safety and risk analysis of complex systems. The features of BN in uncertainty handling, probability updating, and dependency representation make it a very popular tool to model the chemical and process industry.

Since 2012, different reviews of Bayesian Networks applied to Chemical plants began to see the light in the early 2000s. For example, an exhaustive review about the applications of BN for dependability, risk analysis and maintenance

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areas, is presented in Weber, Philippe and Jouffe, Lionel (2006). Also, Zerrouki and Smadi (2017) presented an overview of the application of BN in risk analysis and accident modelling in chemical and process industries during a period of 10 years (2006-2016). Recently, Yazdi (2019) examined the validity of Bayesian network to build rational consensus in subjective probabilistic failure analysis. Moreover, Kabir and Papadopoulos (2019) presented a review of the applications of Bayesian networks and Petri nets in the field of safety, reliability, and risk assessments.

This work will present a summary of a brief statistical review of the use of Bayesian networks in the chemical and process industry during the period 2006-2018. It is an updated analysis of the work made by Zerrouki and Smadi (2017) with publications related to chemical plants and process industries covering up to 2018.

This paper is organized as follows: The description of the BN methodology is presented in Section 2. Different types of BNs are briefly explained in Section 3. Then, an overview of Bayesian networks applications in chemical plants and process industries is provided in Section 4. Conclusions regarding the distribution of articles are presented in Section 5.

2. Bayesian networks

Bayesian belief network or Bayesian network (BN) is a directed acyclic graph (DAG) that is widely used in different domains such as accident modelling, risk assessment, and maintenance area. BN consists of nodes and arcs; the nodes represent variables and the arcs represent the probabilistic relationship between these nodes (Jensen and Nielsen (2007)). In the graph shown in Figure 1, the arc is directed from the parent node (A) to the child node (B). Each node in the BN has a conditional probability table (CPT) illustrating the relation cause-effect between nodes.

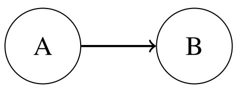

Fig. 1. Example of Bayesian network.

According to the conditional independence and the chain rule, BNs represent the joint probability distribution $P(\mathbf{X})$ of variables $\mathbf{X} = \{X_1, X_2, ..., X_n\}$ of any Bayesian networks as:

$$P(\mathbf{X}) = \prod_{i=1}^{n} P(x_i|pa(x_i)) \quad (1)$$

BNs can update the prior probability of any events given new information (posterior probability), called evidence M by implementing the Bayes' theorem as follows:

$$P(X|M) = \frac{P(X,M)}{P(M)} = \frac{P(X,M)}{\sum_x (X,M)} \quad (2)$$

Note that $P(X,M)$ is the probability of both X and M occurring, which is the same as the probability of X occurring times the probability that M occurs given that X happened: $P(M \mid X) \times P(X)$.

These two equations are the essence of BN, Eq. 1 is used to calculate the joint probability distribution and Eq. 2 to update the prior probability. BN can be used for both qualitative representing by a network structure and quantitative assessment represented by conditional probability tables.

To understand the circulation of the information in the BN, we will give a calculus example in the following; Let us consider the example in Figure 1, in the example below the conditional probability of variable A given variable B, can be calculated as:

$$\mathrm{P}(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{\sum_A P(B,A)}{P(B,A)} \quad (3)$$

Table 1. Unconditional probability table for variable A.

$A = a_1$	$A = a_2$
0.3	0.7

Table 2. Conditional probability table for variable B.

	$A = a_1$	$A = a_2$
$B = b_1$	0.6	0.2
$B = b_2$	0.4	0.8

For illustrative purpose, we propose that the variable B is in the state b_1. Then, given this knowledge, we will update the probability of the variable A being in the state a_2, using Eq. 3 as:

$$P(A=a_2|B=b_1) = \frac{P(B=b_1|A=a_2)P(A=a_2)}{P(B=b_1)}$$
$$= \frac{P(B=b_1|A=a_2)P(A=a_2)}{P(B=b_1|A=a_2)P(A=a_2)+P(B=b_1|A=a_1)P(A=a_1)} \quad (4)$$

We use the conditional probabilities from Table 1 and Table 2, and insert these probabilities into Eq. 4 in the following way:

$$P(A=a_2|B=b_1) = \frac{0.2\times0.7}{0.2\times0.7+0.6\times0.3} = 0.4375 \quad (5)$$

As mentioned before, the result obtained in Eq. 5 is known as the posterior probability. The importance of such result lies in the capability of describing the probability of an event under certain conditions (set by the evidence). This methodology can be implemented for diagnostic (as shown in this example) or prediction (by applying straightforwardly Eq. 1) analyses.

3. Types of Bayesian networks

During this study, we noticed that not only classic BNs were used to carry out each of the analyses on the articles found. The techniques related to BNs taken into account in this work are the Dynamic and Object-Oriented as well as Bow-Tie to Bayesian networks. A brief description of such methodologies is provided as follows.

3.1. *Dynamic Bayesian networks*

Dynamic Bayesian network (DBN) is considered as an extension of static BN. Contrary to ordinary BN, DBN can integrate the temporal evolution of a set of random variables over a discretized timeline in the modelling to describe the dynamic behaviours (Khakzad (2015). DBN is represented by a sequence of time slices, these slices describing the systems state for each time step, the relationship between variables in different slices denote a temporal probabilistic dependence between the variables (Hu et al. (2015)). We can distinguish two types of dependence between variables; the arcs between nodes in the same time slice referred to as contemporaneous dependencies and the links between nodes in different periods are called Non-contemporaneous dependencies (see Figure 2, continuous arcs represent contemporaneous dependencies and the dash-and-dots ones represent Non-contemporaneous dependencies). It is important to note that in DBN, the nodes are connected not only on its parents at the same time slice but also on its parents and itself at previous time slices (Khakzad and Reniers (2016)). For two-time slices modelling, the joint probability distribution of a set of random variables at time $t + \Delta t$, that is $P(Z^{t+\Delta t})$, can be expanded as:

$$
\begin{aligned}
P(Z^{t+\Delta t}) &= P(X_1^{t+\Delta t}, X_2^{t+\Delta t}, ..., X_n^{t+\Delta t}) \\
&= \prod_{i=1}^{n} P(X_i^{t+\Delta t} \mid X_i^t, pa(X_i^t), pa(X_i^{t+\Delta t}))
\end{aligned}
\tag{6}
$$

Where $X_i^{t+\Delta t}$ and X_i^t are the copies of X_i in two consecutive time slices with a time interval of Δt, and $pa(X_i^{t+\Delta t})$ and $pa(X_i^t)$ are the parent sets of X_i at the time slices $t + \Delta t$ and t, respectively (see Eq. 6).

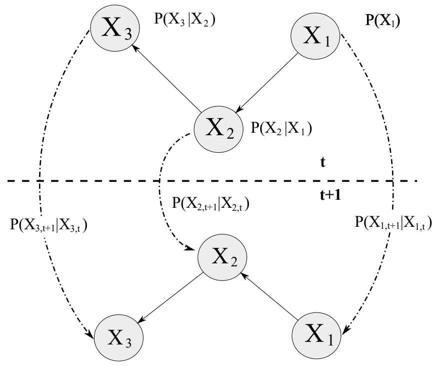

Fig. 2. An illustrative example of dynamic Bayesian network for three variables.

3.2. *Object-Oriented Bayesian networks*

This kind of BNs adopts the Object-Oriented framework (similarly to the programming environment) to model more complex structures than those of traditional BNs in an attempt to speed up the inference process. In this manner, the main architecture of the object-oriented Bayesian network is built in terms of inter-related substructures. Here, the basic element is an ”object” and it has attached ”attributes” that provide the scheme for hierarchies. In addition to that, ”classes” are used to enclose objects with similar attributes and describe them with the same probabilistic model, Koller and Pfeffer (2013). In this type of BN, we can distinguish two kinds of nodes; instance nodes and usual nodes. The latter are nodes that are mostly used in ordinary BN (or DBN). The instance nodes, which are the most important ones in this methodology, represent another BN referred to as sub-network. Therefore, we can extract from above that OOBNs are constructed from a hierarchy of sub-networks with desired levels of abstraction with a view to reducing a large and complex BN to a simple model (Khakzad et al. (2013b)). The new OOBN formed is a small size, an easy communication network with no identical structure (avoid repeating structure). Interface nodes containing input and output nodes are used to connect instance nodes with usual nodes. For more detail about OOBNs see (Kjærulff and Madsen (2008)) (note that in the book OOBNs are called object-oriented probabilistic networks, OOPNs).

An example of OOBN is depicted in Figure 3. As can be seen, both node 3 and 6 are selected as the output nodes (presented in the network with a blue border) in instance A and B, respectively. Also, node 3 and 6 are considered as the input nodes (presented in the network with a dashed border) in instance B and C, respectively. The extracted BN is presented only by instance nodes

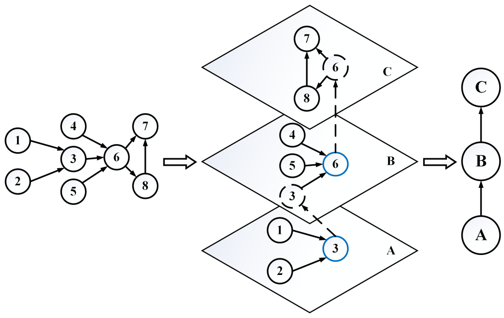

Fig. 3. An ordinary BN in the left side is constructed using hierarchical structures with arbitrary levels of abstraction in the middle and then presented by instance nodes in the right.

A, B, and C (presented in the right side of the network).

3.3. *Mapping Bow-Tie (BT) into Bayesian Networks*

Since bow tie (BT) is a coupled technique that is composed of fault tree (FT) and event tree (ET), it is enough to know how to map BT into BN. Any FT has a corresponding BN based on the work of Bobbio et al. (2001). Also, Bearfield et al. (2005) show how an event tree can be viewed as a Bayesian network. Based on the aforementioned works and the mapping algorithm described in Khakzad et al. (2013a), BT model on the left of Figure 4 is mapped into its corresponding BN model on the right of Figure 4. BT and BN are used together in many articles as shown in Table 7 being the second more used type of BNs. Usually, this methodology is adopted to overcome some limitations that appear in BT such as dependencies between the basic events and the safety barriers and updating probabilities of the events and the consequences.

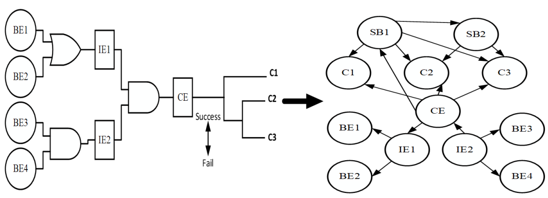

Fig. 4. *Left.* Example of bow-tie model (C; consequence, IE; intermediate event, BE; basic event, CE; critical event, E; event). *Right.* BN model for the BT example in the *Left* (C; consequence, IE; intermediate event, BE; basic event, CE; critical event, E; event).

4. Overview of BN applications in chemical plants and process industries

4.1. *Methodology*

The data used in the present study was derived from different sources such as; Google Scholar [a], Research Gate [b] (RG), Thomson Reuters [c] and National System of Online Documentation of Algeria (SNDL) [d], using keywords being; ”Bayesian network”, ”chemical plants”, ”safety analysis”, ”risk assessment” and ”process safety” as the search topics, a total of 160 publications were found in the database. Reviewed, categorized, and summarized the technical articles published only in scientific journals of Science Citation Index Expanded (conference proceedings and books chapters are excluded). Only the technical articles that have a direct relationship with our study are chosen. The steps followed to form the review, consisted of a collection of data from the sources aforementioned. Then, publications were organized after their collection to leave only the relevant articles ready for classification. After that, we classified them into four categories: by year, by journal, by application domain, by BN type, and by country.

4.2. *Summary of the results*

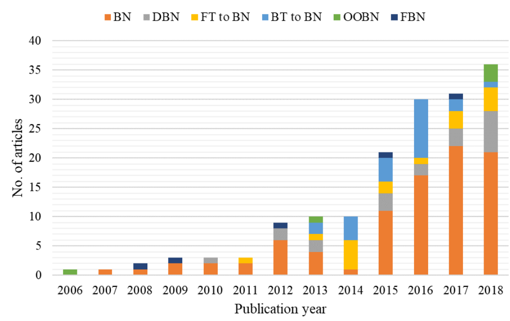

Fig. 5. Distribution of publications of the different types of BN techniques used in the chemical plants from 2006 to 2018.

From Figure 5, we can notice that the publications that used BN in the chemical and process industries witnessed a huge increase particularly after 2012 and after 2013. It can also be observed in Figure 5 that the popularity of this technique has continued increasing over time, being 2018

[a] https://scholar.google.com/
[b] https://www.researchgate.net/
[c] https://www.thomsonreuters.com/
[d] https://www.sndl.cerist.dz/

the year with more publications. This is often due to the comparisons of BN with other methods such as fault tree analysis (Khakzad et al. (2011)) and Bow tie technique (Khakzad et al. (2013a)). The comparisons exhibit the advantages of BN over the aforementioned methods. These advantages can be summarized by the ability of BN to update probabilities of variables, to represent dependencies between these variables, and most important to handle uncertain and complex systems. From Figure 5, we can notice that the publications after 2013 were mainly based on the use of both BT and BN to provide a better presentation of the accident scenario and to update dynamically the different events in the model.

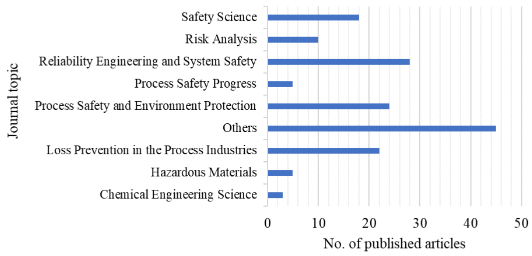

Fig. 6. Journal distribution of the publications of BBN used in the chemical plants from 2006 to 2018.

Figure 6 displays the journals containing the publications that adopted BNs for safety and risk analysis, reliability engineering, and accident modelling in chemical plants. As can be noticed, the vast majority of the papers has appeared in the safety journals instead of chemical journals (Zerrouki and Smadi (2017)). The majority of publications are published in ”Science direct” journals such as ”Safety science” with 18 publications, ”Loss Prevention in the Process Industries” with 22 publications, ”Reliability Engineering and System Safety” with 28 publications, and ”Process Safety and Environment Protection” with 24 publications. Followed by ”Wiley Online Library” among them ”Risk Analysis” with 10 publications and ”Process Safety Progress” with 5 publications.

In Figure 7, we present results from the review of different publications that used BN and their application in the sector of the chemical industry. We noticed that DBN is the methodology more frequently used after the classic BN. The success of such a technique can be due to the capability of modelling the dynamic behaviour of systems. The process of mapping BT and FT into BN is the third and fourth method most adopted after DBN, respectively. This result can show a migration of the use of only BT to a more flexible methodology like BNs. Fuzzy Bayesian Network appears as the last used method probably due to the relatively early implementation of Fuzzy set theory to capture the uncertainty attached to failure events.

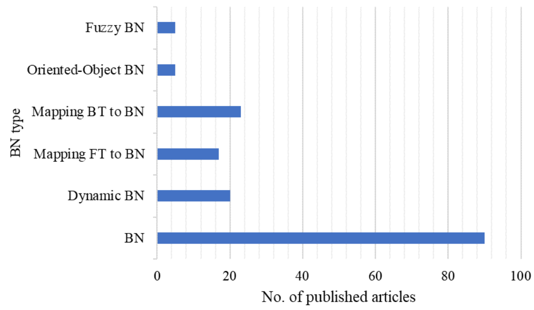

Fig. 7. Distribution of publications by type of BN implemented.

We found from the literature (Zerrouki (2018)) about BN (Figure 8), that a set of 160 articles about the application of BN to the chemical plants and process industries. Most of the references found are about safety and risk analysis, and risk assessment with 20% and 15%, respectively. Furthermore, Figure 7 indicates that a large number of publications used either FT, ET, or BT to build the original model of the study, then the model transformed to BN, which helps to avoid the difficulties inherent to construct a BN model and the problems of fill their CPTs.

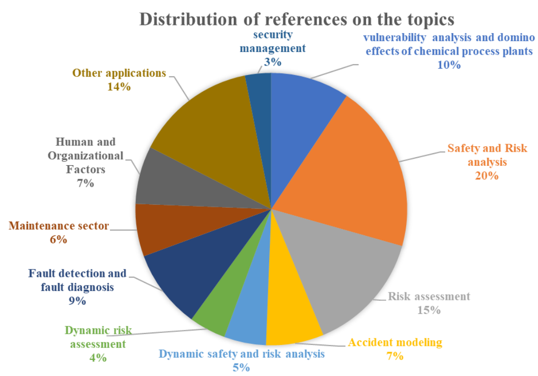

Fig. 8. Distribution of references that used BN in the chemical plants and process industries (2006-2018).

In Figure 9 the most cited authors (i.e., Khakzad et al. (2011); Weber, Philippe and Jouffe, Lionel (2006); Khakzad et al. (2013a,b); Bouejla et al. (2014); Khakzad et al. (2012, 2013c); Abimbola et al. (2015); Yuan et al. (2015) are presented. The graph shows Khakzad et al. (2011), as one of the

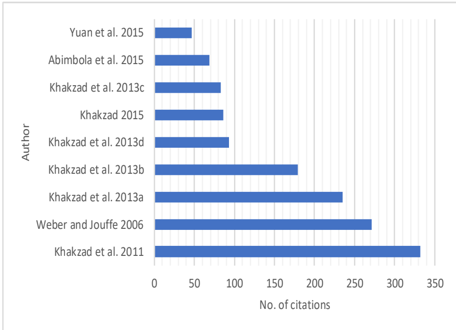

Fig. 9. Distribution of the most cited authors that used BN in chemical and/or process industries.

most active authors in the process industry with more than 300 citations. This author is followed by Weber, Philippe and Jouffe, Lionel (2006) with 270 citations of their paper with an application to a water heater system.

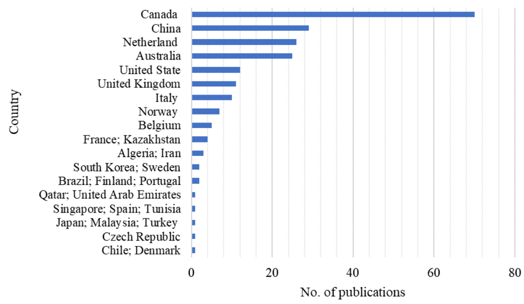

Fig. 10. Number of publications per country in the domain of modelling chemical industry using BN.

Figure 10 displays the number of publications published between 2006 and 2018 per country. We must note that the total number in Figure 10 is higher than the number of publications reported on the other graphs as the authors involved in the same paper were from different countries and that increased the number of counts in the analysis. Figure 10 showed that there is a growing interest in the modelling of chemical and process industries by BN, especially in Canada, Asia, and Europe. A remarkable observation from this graph is that Canada had the highest contribution with 70 publications. Also, it is important to note that more than 86% of publications from Canada were made by Safety and Risk Engineering Group (SREG) from Memorial University of Newfoundland. This is due to a large number of chemical industries, particularly oil and gas facilities existing in Canada. For instance, Canada is the fifth largest oil producer in the world and the fourth largest oil exporter (2017). Moreover, it has the third largest oil reserves in the world. About 5% of total production was produced mostly in Newfoundland and Labrador. Offshore oil facilities on the Grand Banks of Newfoundland are responsible for almost all the crude oil produced. The complexity of these facilities required a high level of safety to avoid catastrophic accident such as the tragedy of offshore drilling rig in the Ocean Range in the Canadian waters. All these factors raised the awareness of the Canadian government to provide the process safety and risk management using different methods such as BN for decision making in chemicals and industrial plants.

Canada is followed by China and Australia from Asia with 29 and 25 publications, respectively. Note that 84% of publications from Australia were made by Australian Maritime College (AMC), University of Tasmania. Thereafter, From Europe the Netherlands have the most contributions with 26 publications, all of them are made by Safety and Security Science Group, Delft University of Technology.

During the study also it was found a trend to the implementation of not only discrete probabilities but also other types like fuzzy sets. Future research will be conducted to include not only fuzzy set theory but also imprecise probabilities. Authors like Tolo et al. (2018); Antonucci et al. (2015); Estrada-Lugo et al. (2019) have started to use the latter concept to represent the uncertainty attached to the Bayesian network models.

5. Conclusions

In this paper, a brief statistical review of the use of Bayesian belief networks in the chemical and process industry during the last 12 years (starting from 2006) is presented. The results showed a significant increase in the publication in this field due to the ability of BN to model complex systems in different domains. A collection of 160 publications about BNs with applications in chemical plants and process industries had been found in the literature, the main results of the current review can be summarized in the following points:

- BNs have proven their effectiveness over well-known methods (i.e. FT, ET, and BT methods). These advantages manifest by the ability of BN to update probabilities of variables and represent dependencies of different events;
- The majority of the papers that used BNs in chemical plants and process industries has appeared in the safety journals instead of chemical journals;
- We noticed that the trend of publications studied are heading towards the use of

DBN instead of BN and this can be explained by the ability of DBN to model dynamic systems. Also, a significant number of publications used BT and BN to benefit from advantages of both techniques;
- The majority of papers used BN for either safety and risk analysis, or risk assessment of chemical and process industries;
- Canada have the highest contribution with regard to the study compared with other countries and the reasons are briefly discussed. Also, it is found that most of the contributions were made by Safety and Risk Engineering Group (SREG) from Memorial University of Newfoundland, Canada.
- Prof. Faisal Khan and Dr. Nima Khakzad were identified as the most active authors using BNs in the industry of process.

This study can be further developed by adding other types of analysis such as number of papers per million population and number of researchers in different countries. Moreover, a bibliometric review using VOSviewer can give a better representation of figures and can be a promising avenue for further work.

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