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Risk analysis in energy projects using Bayesian networks: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

This systematic review summarizes the use of Bayesian networks in assessing risk in the energy sector based on peer-reviewed publications. The interest in risk analysis of the energy sector has increased with the number of energy resources and energy demand due to the need to supply energy with minimized interruptions and avoid hidden costs related to maintenance and recovery from accidents. A Bayesian network is a powerful tool that harmonizes information and expert judgment to evaluate the probability of different scenarios and events, making them helpful in assessing risk in the energy sector. However, their use in other energy systems development, such as oil refineries, nuclear power plants and biodiesel plants, has not been analyzed in a review. A systematic review has identified and appraised studies with Bayesian network applications in energy production, use and distribution for their scope, modeling aspects and use. The review shows that the applications of Bayesian networks in the energy sector can be improved regarding modeling choices, and recommendations for future works are drawn to aid the standardization of modeling practices.

1. Introduction

Technological development has brought us many new ways of living and solutions to make lives more comfortable. To operate these technologies, however, society needs uninterrupted energy, and guaranteeing its continuous supply is a priority for modern civilization, including enhancing efficient energy use and developing new sources for future use [1]. In this context, constant assessment of new and existing infrastructure in the energy sector is necessary for a reliable energy system due to the worldwide economic significance of energy production [2].

Therefore, researchers and operators rely on modern monitoring methods that provide information about the performance of a system and describe the state of service. These methods help to reduce costs, maintenance time and undesired events such as accidents in energy projects and infrastructure, keeping levels of risk at an acceptable level [2,3]. Risk regulates many aspects of modern life, which has led society to develop complex organizations to evaluate, communicate, and mitigate risk [4].

Several methods are known to analyze the probability of unwanted events and project risk, including classical statistics, expert judgment and Bayesian methods [3]. Risk analysis methods are used in different contexts and help to reduce failures, accidents, economic drawbacks, environmental burdens of a range of energy-producing technologies and processes [5], and social inequalities [6]. They are often embedded in the decision-making process of stakeholders [2].

Specifically, Bayesian Networks (BN) have been widely used for complex risk assessment problems [7]. Based on graphical inference, BN can depict cause-and-effect relationships among variables or events. When applied to unknown incidents, BN can predict its probability, or this probability can be updated when it comes to some previously known circumstance [1].

Since the use of BN is diverse, it is of scientific interest to identify the factors underpinning its application and to understand the focus, main risks and events analyzed with this methodology and how it is applied within the energy sector. In fact, with the increasing importance of the energy sector and the growing need to understand and characterize the uncertainties and adversities within energy systems, the application of BN has continuously increased in the last decade. They can help decision-makers make informed decisions about energy investments, energy policy, and energy operations by allowing for the analysis of possible scenarios and the estimation of probabilities of different outcomes. They also provide a means for integrating multiple sources of

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data and knowledge about energy systems, making it easier to identify cause-and-effect relationships and predict future energy behavior. This can lead to more efficient and effective energy systems that better meet the needs of consumers and the environment. For this reason, reviewing its use in the energy system will support future users in defining the scope and better handling their models.

With that in mind, this review aims to screen and map the scientific applications of Bayesian networks in the energy sector regarding their focus, model establishment, procedures and types of risks presented in the literature.

Therefore, a systematic literature review was conducted in this study using Scopus and Web of Science on peer-reviewed papers published from 2017 to 2022.568 articles were identified, screened for their fit to the scope of this study and 145 records were analyzed in full. Based on previously established criteria, 118 studies were included in the thorough analysis to evaluate their contribution to the risk assessment in the energy sector.

The present study is divided into 5 sections. Section 2 introduces the main concepts related to Bayesian Networks. The adopted methodology is presented in Section 3. Section 4 presents the results of the review, and finally, Section 5 discusses the results. Section 6 briefly concludes the study.

2. Bayesian networks

BN is based on the Bayes theorem and is a graphical, mathematical model that represents the probabilistic relationships between nodes or variables. Since the advent of new computational capacities, BN has become popular in the decision-making process in various domains due to its ability to deal with high-complexity problems [8]. Fig. 1 shows an example of a BN. The example shows the constituents of a BN: 1) a directed acyclic graph that defines the dependency between the nodes (or variables) and 2) the quantification of the dependencies in the form of conditional probabilities [9].

Each variable is represented by states with two possible values, true or false. However, the variables can take more than two states and even have a continuous nature [10,11]. The arcs (arrows) in the BN specify the dependence among variables and guide the probability distribution among the random variables [12].

Each of the nodes in a BN has a specific probability distribution. An arc - (I,J) - express a dependence relation between nodes I and J, indicating that node I is the parent of the node (child) J, which implies that node J is affected by node I. When constructing a BN, it is necessary to inform the unconditional probabilities of all nodes and the resulting conditional probabilities of all child nodes, given all possible combinations of their direct parent nodes [12]. Equation (1) shows the calculation of the conditional probability of child nodes based on the states of each parent node:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i | X_1, \dots, X_{i-1}) = \prod_{i=1}^{n} P(X_i | Parents(X_i)) \tag{1}$$

Although BN allows for calculating the conditional probabilities of the child nodes in the network based on the probabilities of the states in the parent nodes [12], challenges remain when constructing a BN. When databases with valuable information are available, the automation of constructing conditional probability tables (CPT) is possible [8]. However, this is not the case in many situations, and experts' opinions must be used to define the CPT manually [8,12]. The number of experts, nonetheless, depends on the modeler's choice. Examples with 3 experts [13,14], or 22 [15] are found in the literature.

In this context, it is necessary to elicit data from experts to define the CPT manually. However, given that the complexity of defining CPT increases exponentially, for large-scale BN, it becomes intractable to define all the probability functions that compose each CPT manually. Several methods are available to define the probabilities of each state in the child node without eliciting each value from the experts. A few examples are the ranked nodes method (RNM) [7], the weighted sum algorithm (WSA) [16] and an adaptation of the analytic hierarchy process (AHP) method [17]. These methods are further explained in Ref. [8].

2.1. Steps to build a bayesian network

The construction of BNs starts by defining the objectives of the model (Fig. 2). In risk analysis, modelers need to identify what risk is being analyzed, either "risk of" or "risk to." Without a clear objective, the model outcome could be biased, or its use could be compromised. It is also essential to define the time horizon and geographic levels of the proposed model [18,19].

With a well-defined objective, a conceptual model is needed, i.e., a conceptualization of the influential aspects of the defined problem. After establishing a conceptual model, a group of experts, modelers and stakeholders will define the variables that influence the problem.

After describing the variables in the model, the modeling team should define the variables and their interlinkages based on unidirectional arcs [11,18]. This is the definition of the influence diagram since BN is a causal framework where V1 influences V2, as shown in Fig. 1. It is crucial to remember that BN is an acyclical graph, meaning it does not allow loops back into the model. One of the goals here is to minimize the number of connecting arcs, searching for the simplest structure of connections and links between variables.

Each variable of the BN, or node, represents observable events of measurable processes, which in many cases are continuous variables. Variable states might be.

- Boolean when it takes only two values, such as true or false;
- Categorical, when defined by categories like low, medium or high;
- Discrete;
- Continuous.

Although discretization of continuous variables is not necessary, their use in continuous form is a limitation in computation and programming algorithms and reduces time demand when computing probabilities using expert judgment. There are several ways to discretize variables, such as equal distance and equal frequency intervals, or elicited from experts [9].

The defined states will serve as a parameter for experts to estimate the CPT or guide the algorithm when data is available. As mentioned in the previous section, the CPT describes the probability of a child node or variable being within a state, given a combination of parent state values [19,20].

The next step is to evaluate the model and its applicability through

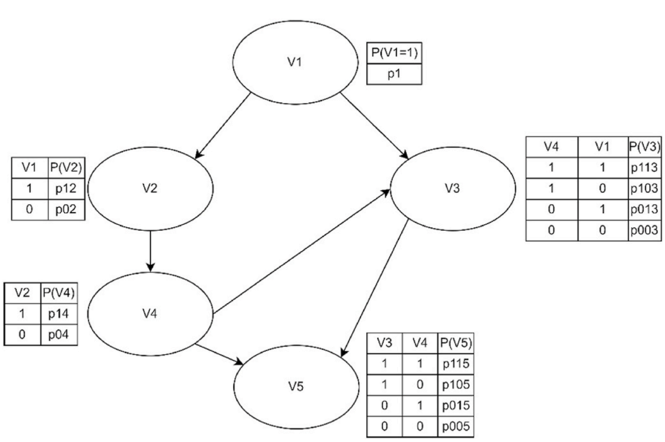

Fig. 1. Example of a BN network with 5 nodes and the conditional probabilities of each node.

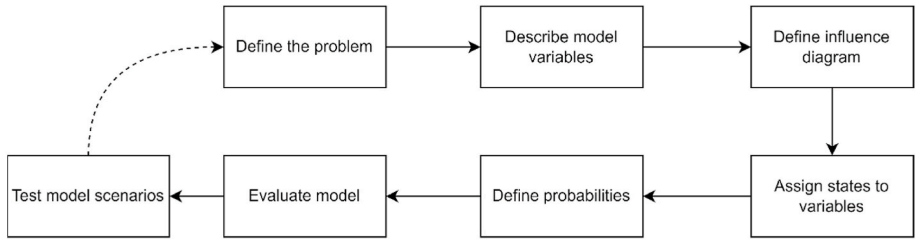

Fig. 2. Steps to build a Bayesian network.

validation. Kaikkonen et al. [9] explain the existing methods for model validation, which can be divided into.

- "Train and test," when the performance of a data-based model is evaluated against other data sets not included in the modeling process;
- "Cross-validation" is when database pieces are removed repeatedly, and the constructed model is tested against the excluded data.;
- "Expert evaluation", is when expert judgment is used to evaluate the model results.
- "Sensitivity analysis", which tests the strength of the links within the model and the value of information;
- Goodness-of-fit, which identifies the model's capacity to predict the same data used to build the model.

Finally, the application of the model will provide the expected analysis. For model use, four categories are used. When modelers compute posterior probabilities, model use is classified as inference, evidence propagation or belief upgrading [21]. Another option is characterization when no previous probabilities exist on the problem at hand, and BN is used to obtain the first result. In the end, if there are inconsistencies or unrealistic results, modelers might restart the process, back to redefining the model's objectives.

These steps are translated into attributes to aid the evaluation of the BN construction in the reviewed studies and will serve as a basis for analyzing the publications and recommendations for future applications of BN in the energy sector.

Source: Based on [22].

3. Review methodology

A systematic review is a comprehensive, structured, systematic examination of the existing evidence on a particular research question. It is evidence synthesis involving a thorough search, critical appraisal, and synthesis of relevant studies to answer a specific research question. A systematic review aims to provide a comprehensive, transparent, and unbiased summary of the current evidence base on a particular topic. They are considered the highest level of evidence in the hierarchy of evidence and are widely used in health and social sciences research to inform clinical and policy decision-making. This review aims to summarize the use of BN in the energy sector, providing an overview of the practice and applicability of this methodology in the energy sector. The parameters established for this review are shown in Table 1.

The application of BN in the energy sector has a wide range of objectives, such as blowouts during the drilling of oil wells [5], accidents in natural gas stations [23] and economic risk assessments [14]. However, many of these applications lack proper reporting of methodological choices made. Therefore, this review analyses the literature to provide future research with insights and recommendations for a suitable description of BN implementation. This work used the following systematic review methodology to analyze the use of BN in energy studies properly.

The search for articles was conducted on Web of Science and Scopus in January–February 2023. The search strings were defined as "energy Bayesian network risk" to explore the studies that apply BN in the energy sector context. This review only focuses on articles in English from 2017 to 2022 and published in peer-review scientific journals.

Table 1
Systematic review protocol used in this study.

Description	Review of papers using Bayesian networks to assess technological development risk
Objectives	This review aims to identify the uses of Bayesian networks and causal maps to assess technological development risk in the energy sector and to identify which variables affect their development the most.
Keywords	Bayesian networks; Bayesian causal maps; risk assessment; technology risk; energy sector
Source Engine	Scopus; Web of Science
Source Selection Criteria	English; between 2018 and 2022.

The process of article selection is shown in Fig. 3 (left). First, articles were screened by title and abstract to check for their fit to this study's objectives after removing duplicate records. To be included in the review, the articles had to analyze some risk aspects of an energy system, infrastructure, economic viability or any other application of the BN model to risk assessment within the energy sector. From the 832 records found in the searched database, 645 were excluded from the analysis for not dealing with the energy system.

After screening each abstract and title, the remaining 187 records were screened. 69 articles were excluded in this step of the review. From these, 6% were removed because they were reviews, 11% of the texts were unavailable for download, and 83% used different Bayesian methods for analysis other than the network.

Therefore, 118 publications were selected for further analysis. These publications were screened based on the steps for building a BN explained in section 2.1 to determine the quality of the application of BN in the energy sector. The articles were screened for the sector of interest, type of risk analyzed, the objective of the model, variables used in the model, who selected the variables and source of information for the selection, who defined the interlinkages between the variables and the source of information for the definition of the interlinkages of variables, who and how the conditional probabilities were defined, the number of experts involved in the framing of the model and the type of BN used in the analysis. Table 1 shows the attributes analyzed in this review.

4. Results

4.1. Scope of analyzed models

The 118 articles included in the analysis presented a variety of risk assessments in different domains and sectors. Fig. 4 shows a word cloud of the focus of each article regarding the risk they intend to investigate. The most targeted types of risk can be seen in this word cloud and are heavily focused on oil&gas and nuclear power chains, involving infrastructure of oil wells, such as the risk of oil spills and oil well blowouts, gas pipeline leakages and accidents in nuclear power plants. For example [5], used BN to analyze the risk of an offshore well blowout

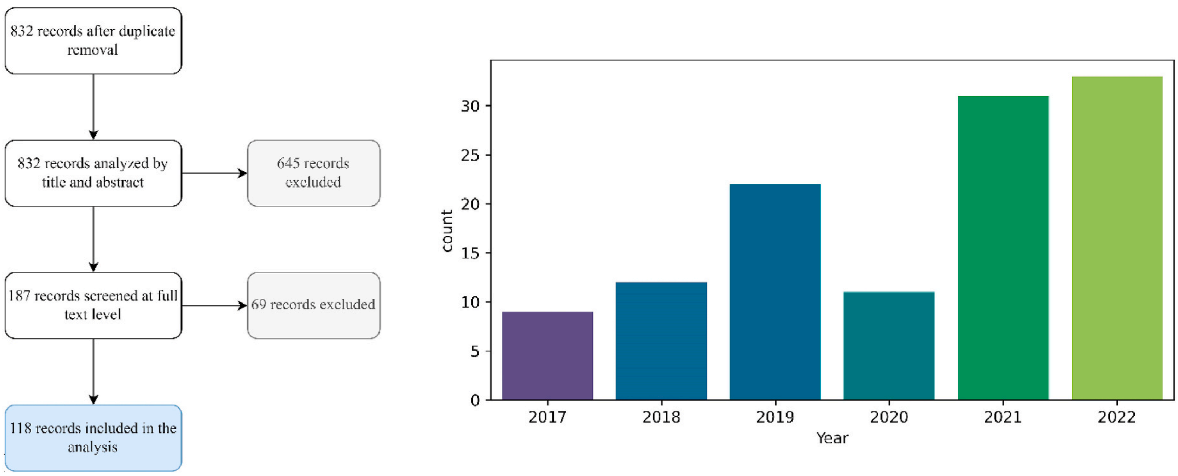

Fig. 3. Step-by-step process for literature screening (left) and papers included in the analysis by year (right).

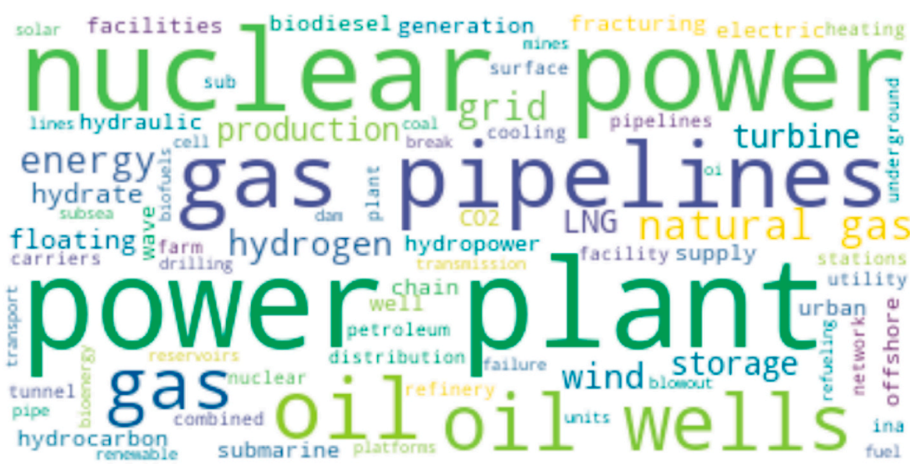

Fig. 4. Word cloud of risk assessments in the energy sector of the articles included in the review.

during drilling, and [24] investigated the risk of an oil well blowout during managed pressure drilling. In nuclear power plants, the examples range from seismic failures [25], vulnerability to floods [26], software reliability of digital instrumentation [27] and cyber-attacks [28].

Each article was also classified into the categories in Table 3. Categories are split into "risk of" and "risk to," according to the type of risk assessed in each article. While "risk of" studies investigate the influential factors on the risk of events, "risk to" analyses involve identifying and assessing potential risks, developing strategies to mitigate and manage those risks, and ensuring that the system can withstand and recover from disruptive events. For example, "Risk to resilience" refers to the transformation from a state of vulnerability to a state of robustness, where systems can withstand and recover from potential adverse events. Sarwar et al. [29] focus on the resilience analysis of an offshore oil and gas facility. The authors use a risk analysis approach to identify potential risks to the facility and develop strategies to enhance the system's resilience during a potential hydrocarbon release.

Accidents, leaks, cyber-attacks, oil spills, and structural health are some risk categories on which the articles in this review focus. Although a leak or an oil spill might be considered an accident, most of the time, authors did not specify the type of accidents they were referring to, and their risk analysis focused on a general risk of accidents. When a specific accident was mentioned, they were split into different categories.

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Each article was attributed to a sector within the energy domain, and the risk assessments were classified into the risk classes shown in Table 2, which are presented in Fig. 5. It is important to note that the risk classes shown are not limited to one per article, but instead, they are related to the factors that influence risks taken into account within each proposed model. Despite the broad range of risk assessments, there is a high concentration of studies in the technical risk domain applied in the oil & gas industry and nuclear power plants, followed by environmental risk assessments involving the oil&gas and nuclear industries.

88% of the articles in the review addressed some technical parameters to assess risks in the oil & gas and nuclear power plants. One example is the work of Sarwar et al. [29], who evaluated hydrocarbon release based on technical aspects of offshore oil & gas facilities design, such as the platform hose connection system, valves control, and telemetry system and equipment vibration. Groth et al. [30] used technical parameters of a nuclear power plant like cold pool temperature and level, peak coolant temperature, cover gas pressure and Doppler feedback reactivity to investigate the risk of accidents.

Table 2
Attributes, their related questions and the class of each attribute analyzed in this review.

Attribute	Question	Class
Sector	Within the energy sector, what is the main focus of the article?	Oil & gas, nuclear power, electricity in general, hydrogen, wind turbines, energy systems in general, Carbon Capture and Storage (CCS), biodiesel, gas turbines, combined cooling, heat and power, renewable energy, wave energy and biofuels in general.
Objective of the study	What is the main focus of the article?	Several possibilities – Word cloud result
Risk class	What type of risk is being studied?	Technical, environmental, safety, social, economic, political, legal
Variables	What variables were included in the model?	Several possibilities – word cloud result
Model framing – Who[a]	Who selected the variables in the model?	Modeler or modeling team one-disciplinary (MO)/Modeling team multidisciplinary (MM)/External expert or expert team one-disciplinary (EO)/External expert team multidisciplinary (EM)/Non-expert stakeholders (SH)/No information (NI)
Model framing – Source of information[a]	How were the variables selected?	Learned or modeled based on data (DL)/Literature-based (L)/Expert judgment (EJ)/Non-expert judgment (NJ)/Other (O)/No information (NI)
Model structure – Who	Who participated in defining the links between variables?	Modeler or modeling team one-disciplinary (MO)/Modeling team multidisciplinary (MM)/External expert or expert team one-disciplinary (EO)/External expert team multidisciplinary (EM)/Non-expert stakeholders (SH)/No information (NI)
Model structure – Source of information	How were the links between variables defined?	Learned or modeled based on data (DL)/Literature-based (L)/Expert judgment (EJ)/Non-expert judgment (NJ)/Other (O)/No information (NI)
Probabilities – Who	Who participated in producing the probabilities?	Modeler or modeling team one-disciplinary (MO)/Modeling team multidisciplinary (MM)/External expert or expert team one-disciplinary (EO)/External expert team multidisciplinary (EM)/Non-expert stakeholders (SH)/No information (NI)
Probabilities – Source of information	How were the probabilities produced?	Learned or modeled based on data (DL)/Literature-based (L)/Expert judgment (EJ)/Non-expert judgment (NJ)/Other (O)/No information (NI)
Discretization	How was discretization done?	Learned from data by an algorithm (DL)/Based on data-analysis (incl. literature) (DA)/Elicited based on expert knowledge (EE)/Elicited from non-expert stakeholders (ES)/Equal Distance Interval (EDI)/Equal Frequency Intervals (EFI)/Other (O)/No information (NI)
Validation	What type(s) of validation method(s) is (are) used?	Train & Test (TT)/Cross Validation (CV)/Expert evaluation (E)/Comparison to previous models (PM)/Sensitivity analysis (SA)/Goodness of fit (GF)/No validation (NV)
Model Use	How is the study's model used to answer the research questions?	Inference (I)/Characterization (CH)/Other (O)/Not applicable (NA)
Number of experts	How many experts were involved in the construction of the model?	Number of experts involved/No experts involved (NE)/No information (NI)
Type of BN	What type of BN was used in the model?	Types of BN (shown in the results)
Intended end-user of the model	Who is the intended end-user of the model?	The model developers themselves (MD)/Other scientists (OS)/Decision-makers (incl. Planners and managers) (DM)/Stakeholders (SH)/Teachers (T)/Common public (CP)/Not clear (NC)

Table 3
Risk focus of the reviewed articles and each occurrence that falls in each category.

Risk of	References
Accidents (including fires)	[3,23,26,30,35,48–50,52,53,56,58,60–62,68–87]
Leaks	[40,51,57,88–92]
Cyber attacks	[27,28,47,93–95]
Failures and faults	[38,39,41,42,44,63,65–67,96–104]
Oil spills and blowouts	[5,24,37,105–107]
Seismic hazards	[25,108,109]
Risk to	
Performance	[34,110]
Resilience and reliability	[1,29,64,111–114]
Security, safety and human error	[2,15,36,115–118]
Structural health	[59,119–126]
Investments	[14,31,127–129]
Other risks (including multi-risk)	[13,32,43,54,130–137]

On the other hand, few studies focus on assessing the risk of renewable energy, with 11% of the articles in the review. Biofuels, for example, are analyzed by Sajid et al. in three different publications [13,31,32], which focus on biodiesel economic risk, the impact of coronavirus on the sustainability of the biomass supply chain and the performance of biodiesel.

4.2. Variable selection

The evaluation of BN models in this review started with the variables included in the model, who selected these variables and the source of information used to include each variable in the model framework. Fig. 6 shows the word cloud of variables in the studies included in the analysis. As can be seen, technical variables related to corrosion, pressure, valves, sensors, temperature, the flow of fluids of energy infrastructure and domain-specific instrumentation, computation and automation are included in the BN models to evaluate the risk of failure, leakages and safety in energy systems operations. Although human error is the most prominent known factor in the case of accidents in the oil-&gas industry [33], for example, only 10% of the analyzed studies included this variable in their models.

These variables are selected mainly by the modeling groups themselves (Fig. 7), with 87% of the articles depending on the knowledge of their authors to establish the model framework and in the majority of the studies (82%), these modeling groups are composed of people involved in one area of expertise, for example, engineering. Most of the time, these modelers take information from existing data (Data from the Literature DL) to verify the effect of each variable on the risk being

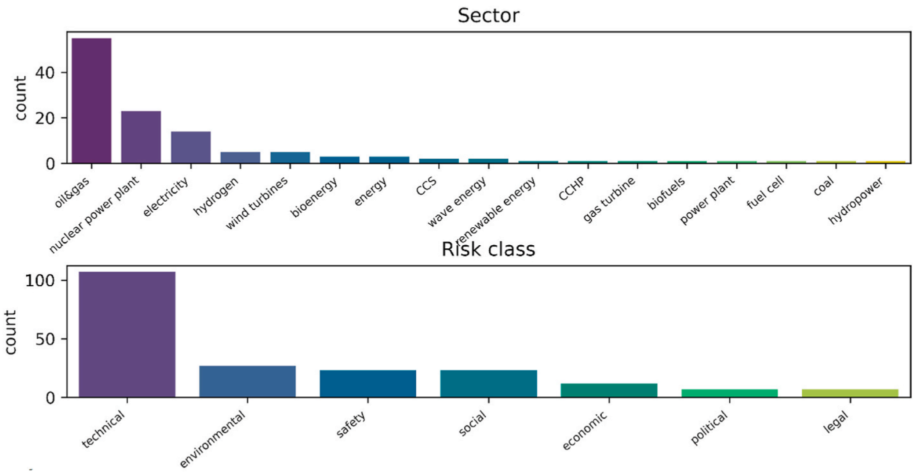

Fig. 5. Sector (top) and risk class (bottom) of the selected articles.

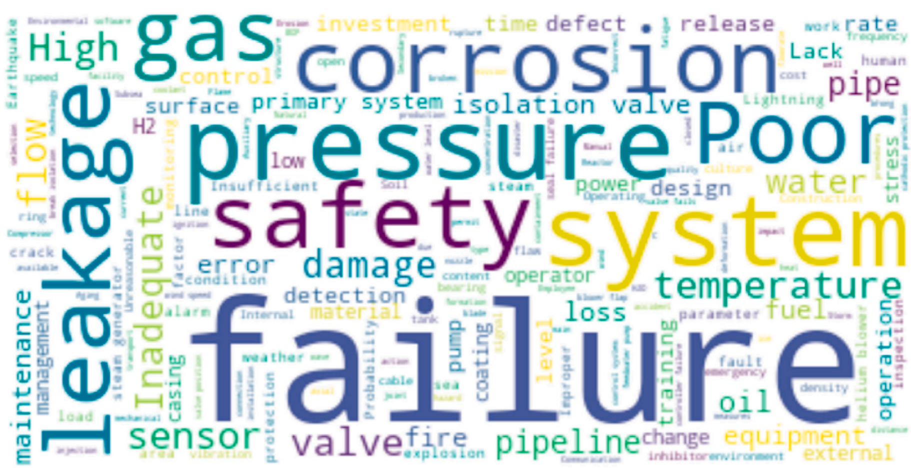

Fig. 6. Word cloud of variables included in the BN model for risk assessment in the energy sector.

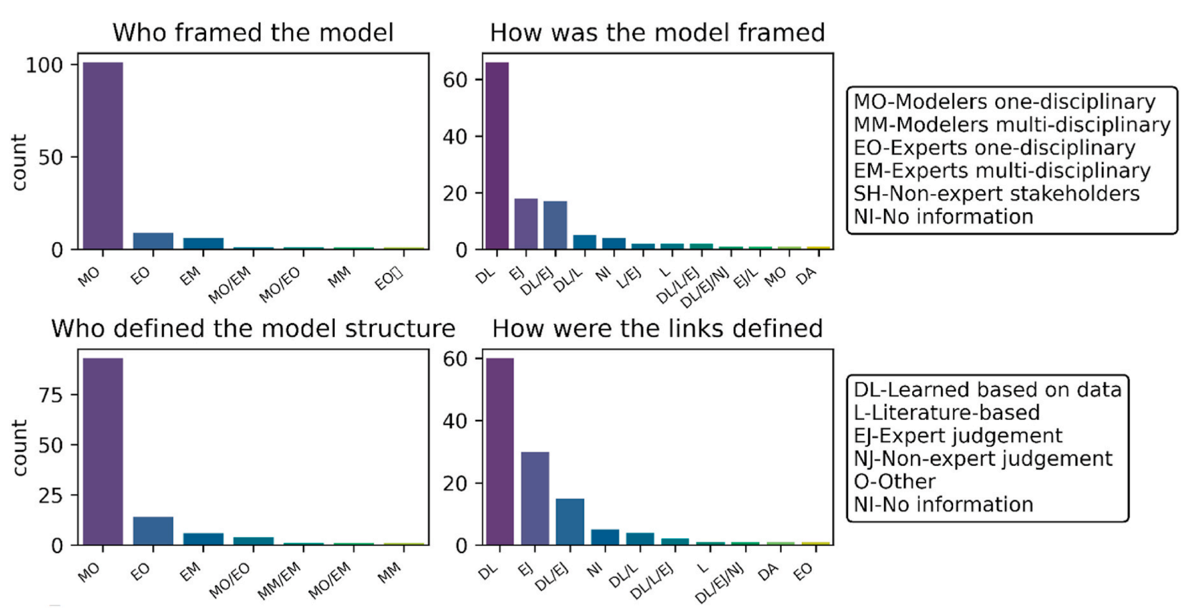

Fig. 7. Who selected the variables in the BN model (framing, top left), how the variables were selected (top right), who defined the links between the variables (model structure, bottom left) and how the links were defined (bottom right).

assessed. Another option widely used is the mixture between expert knowledge and data available (DL/EJ). Expert judgment is used mostly when data is unavailable or to fill missing gaps. For example, Ashrafi [34] had data indicating an operating or failed state of components in petroleum refineries. On the other hand, for variables related to human error in individual, group, organizational, and environmental segments of the model, experts' elicitation had to be used to fill in the missing values of the CPT developed by the author.

In their majority (78%), BN links have been determined by modelers. Again, expert judgment was used to fill gaps in the existing data.

Although risk assessments are a multivariate problem in most cases, the use of multidisciplinary teams to define the variables and their links appears only in five studies [2]. in their application of the BN model to assess the risk of human safety in energy production units [35], in their analysis of single-phase grounding of power transmission lines [36], who studied the risk of nuclear proliferation [37], in their study on oil spills; [34], who analyzed the risk of hydro desulphurization technology in oil refineries. Note that there is a difference between modelers selecting variables based on expert judgment and having the experts build the framework of the model based on their knowledge. This differentiation appears in the articles when the authors mention that variables were selected "based on the expert judgment" or "experts selected the variables."

4.3. Produced probabilities

The quantifiable portion of a BN model is the definition of CPT. It specifies the probability of an event based on the occurrence of other events. In the case of child and parent nodes, the number of probabilities to be determined increases exponentially with the number of influential variables or child nodes. Fig. 8 shows who and how the probabilities were estimated in the reviewed articles. As for the variable selection, the modelers mainly estimated CPT using data or data with some input from experts' judgment.

From the full-text analysis, it was possible to perceive that the articles focused on technical issues or included technical variables such as digital control and automation sensors information. Most papers used auxiliary methods to analyze risk and translate the structure of these methods to BN models. Fault-tree [1,38], Event-tree [39], Bow-tie [40,41], GO model (or GO-FLOW) [42,43], structural reliability analysis [26], failure mode and effects analysis [23], and Living Risk Assessment framework [44] are some examples of risk analysis methods that served as a basis for the construction of the CPT and structure of BN models used in the articles reviewed.

On the other hand, examples show that merging other methods with expert judgments with multidisciplinary points of view is possible [35]. show a robust methodology to define the CPT using the Delphi technique (an expert-based process used to gather and arrive at a group opinion or decision by a survey [45]), which guarantees a more robust and more straightforward definition of the produced probabilities in the study.

4.4. Model handling

In modeling studies, it is essential to explicitly explain the premises and data used in the construction of the model and how it was handled to avoid bias from the reader. However, the analyzed articles in this review lacked the reliability and transparency necessary for scientific communication since reproducibility is compromised when incomplete information on the methodology followed to construct the model is provided [46]. Fig. 9 shows the discretization (top), model application (center) and model validation method (bottom) of the articles included in the review. For intended end-users of the model, number of experts involved and BN type, see Fig. 10.

First, discretization is an important task of BN because it influences the construction of the CPT. In many cases, true/false variables are used, and no discretization is needed, but no explanation is given on this matter, which makes it harder for the reader to understand the true class of the variable. Moreover, 46% of the articles presented no information (NI) about the method to discretize the variables used in the BN models. However, examples of good practices are found in Refs. [30,47], which clearly state the discretization method used, which in these cases was the equal distance method.

Second, when applying the model, most papers used BN to make inferences about the variable representing the risk being analyzed, followed by characterization of the risk, i.e., the first estimation of the risk under interest. However, there is a lack of proper communication of this objective within the studies. Most of the articles assume that BN is applied for inference and forget to specify inference in the statement of their objectives.

Lastly, validation in the BN model is a sensitive issue. Fig. 9 shows that 39% of the studies in the review did not validate their models, while 28% used sensitivity analysis as a validation method.

4.5. Model value

60 out of 118 articles mention that BN would help the decision-making process or support decision-makers with their work, and most of the time, models are constructed using a sector-specific database or from a case study.

One issue with the value of the models created in the studies reviewed is the unclear method for expert judgement elicitation. Even though Figs. 7 and 8 show considerable expert support for defining the variables, structures and constructing the CPT in each model, the majority of articles (58 out of 118) do not specify the elicitation method,

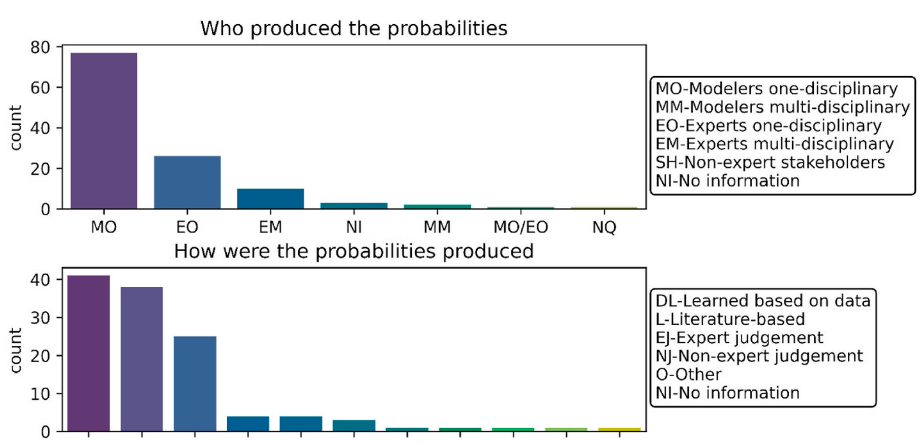

Fig. 8. Estimation of probabilities, who produced them (top) and how they were estimated (bottom).

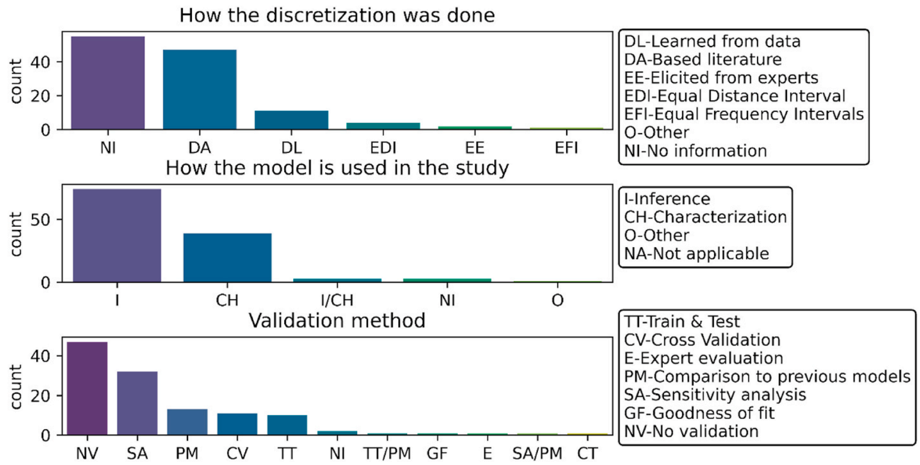

Fig. 9. Discretization method (top), application of the model (center) and validation method (bottom).

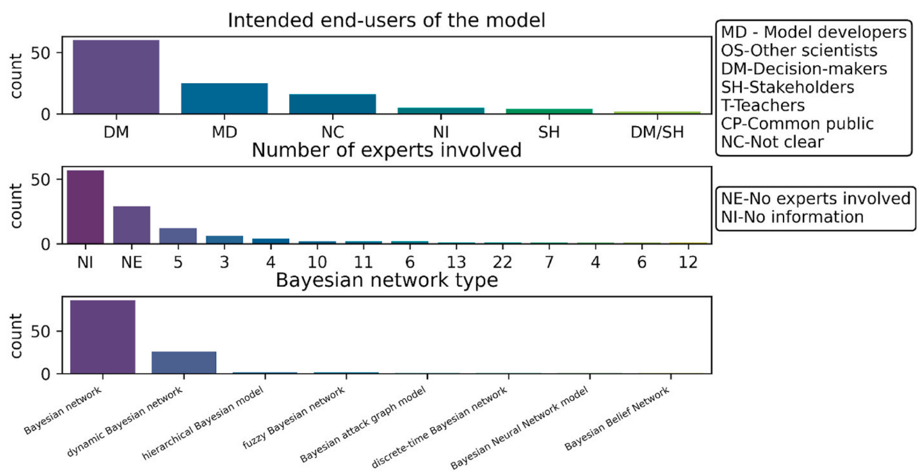

Fig. 10. Intended end-users of the model (top), number of experts involved (center), Bayesian network type (bottom).

how the data obtained was handled or even the number of experts that have been elicited to build the model. In contrast [36], explicitly disclosed how, who and why the experts were elicited and presented the second highest number of experts elicited, with 13 in total, behind [15], with 22 experts included in their study.

Finally, 74% of the studies choose static BN when it comes to modeling risk in energy, which alone does not implicate a low-value model. However, energy systems are dynamic and, in their majority, creating a dynamic model would make it more complex but closer to reality. Authors like [48,49] mention dynamic models as steps for future research.

5. Discussion

5.1. The most relevant studies in the field

To highlight the most prominent studies in the field, this section analyses the most relevant studies based on their number of citations based on the Web of Science and Scopus database.

Two references stand out due to their influence in other publications in the field. Wu et al. [50] employ BN to analyze natural gas pipeline network accidents using the Dempster-Shafer evidence theory to weigh expert knowledge. The authors have 108 citations, representing the highest citation in the dataset. Chang et al. [51], with 43 citations, study the risk of hydrogen leakage in hydrogen generation units based on a dynamic Bayesian network built using data and expert knowledge.

Indeed, both studies reflect the use of Bayesian networks in energy systems in their technical aspect and focus on accidents and leakages. However, while Wu et al. [50] analyze the oil& gas sector, Chang et al. [51] stand out for their application in hydrogen production.

5.2. Application of BN in the energy sector

Energy is a part of the everyday life of most humans and is the result of complex systems development, which are not immune to several classes of risk (technical, environmental, economic and so on). Therefore, the literature on risk assessment of energy production, distribution and use includes various types of risks from technical, economic, environmental, safety and other areas, showing the broad application of BNs in energy risk modeling.

BN is an appropriate methodology to analyze risk since it is anchored on stochastic events and allows an event to happen conditioned to other events. It allows for an investigative process of causality and provides means to prevent catastrophic or damaging events. For this reason, some of the publications in this review might focus on some adjacent activity, such as the work by Ref. [52]. The authors focused primarily on vessel allision near offshore wind farms. Therefore, the variety of applications in the energy realm can hamper the generalization of the analysis of this review, and the inclusion of such studies is subjective and open to criticism.

Although BN is helpful for risk assessments, the application of this methodology is extraordinarily case-specific, and its replicability is not possible due to the different factors influencing each type of risk. Hence, the resulting BN model is completely different even when dealing with similar risks. Considering the works by Refs. [5,25], both studies analyzed the risk of an oil well blowout during drilling but resulted [25] in two different model structures in terms of the number of variables, types of variables and interlinkages between variables as well as CPTs.

As mentioned, BN is a flexible tool for risk assessment in terms of the type of risk and the activity it models. Nonetheless, what catches attention is the concentration of studies on accidents, infrastructure vulnerability and failure of safety systems within the energy sector, especially in the oil & gas sector. With the current changes expected in the energy sector due to climate change and other global issues such as pollution and international and regional conflicts over resources, one could expect that more environmentally friendly energy options would be the focus of risk analysis, like the ones done by Ref. [53] (renewable energy) and [31] (biodiesel), or such as the one done by Ref. [54], who investigated the impacts of social and environmental conflicts on energy projects.

5.3. Modeling aspects and implementation technicalities

Considering the diversity in the articles and models studied in this review, they provide an overview of the implementation techniques of BN models. In their majority, models are based on expert judgement in at least one of the steps of the modeling process, either selecting the variables, defining the links, creating the CPTs or even validating the model. However, some improvements are still necessary in terms of transparency on expert selection, such as who they are, how they were selected and even how many experts took part in the model construction process. Future authors using BN should follow guidelines for expert elicitation [55].

Discretization is another critical aspect of BN modeling that authors ignore, even when the BN is discrete. Discretization makes the construction of CPT easier, especially when involving expert judgment, because it allows for the application of probability estimation using simplifiers, such as the ranked nodes method (RNM) [7], weighted sum algorithm (WSA) [16], and the analytic hierarchy process (AHP) method [17]. In discrete models, the process of CPT elicitation grows exponentially with the number of nodes without applying such methods; therefore, discretization helps reduce experts' mental load. However, selecting a discretization method that reduces the loss of information, clearly states how discretization was done and maintains the representation of relevant changes in the system being assessed is vital.

Another important aspect of modeling overlooked and underreported by authors, which has also been noticed by Ref. [9] in their review, is model validation. Sensitivity analysis was often used where validation was reported, followed by a comparison to previous models. Nevertheless, validation should be encouraged to guarantee the applicability of the models to real-world situations.

5.4. Authors' perception of the pros and cons of developed models

Each article included in the review was screened for the pros and cons of the models built. Generally, the features of BN models that make them suitable for risk analysis have been pointed out as pros of the usage of BN in the specific objectives of each study. Diagnosing system failures [30], determining the likelihood of various events under uncertainty [56], the interconnection between risk factors [29], incorporating a wide range of contributing factors ignored in previous studies [57], evaluating the accident evolution process and accident consequences [58], useful as a post-auditing tool to evaluate progress in mitigating risks [49], qualitatively and quantitatively analyze cause factors in emergency processes [48], adapt to missing data [59], incorporation of diverse data streams [60], are some of the pros mentioned by the authors.

On the negative side, authors have stated cons that are intrinsic to BN models in general, such as applying to a particular country [3,61], using simple or generic scenarios [52], subjectivity due to the inclusion of expert judgment [62,63,64,36,54], need for real-world field data application [65], high computational effort [26], lack of accurate data [66], difficulty in obtaining data from real-life applications due to confidentiality [67], limited risk categories [68,41,36], not including experts from multi disciplines [31], use of generic data [69].

5.5. Recommendations for future research

In this section, the recommendations for future research found in the articles are summarized and displayed in Table 4. The topics included are not exhausted of all possible BN developments when applied to the energy sector, and some of these could also be generalized to applications of BN in other sectors.

Dynamic models and using continuous variables are improvements to BN models that help BN model reality more precisely since many of the issues influencing risk in the energy sector are dynamic and continuous. Therefore, static and discrete models could represent an oversimplification of events.

Data availability is another issue in the construction of BN models, which also leads to the necessity to include expert judgments in the construction of the model, leading to subjectivity issues. In the reviewed articles, the need for more data has been pointed out as an important future development in BN. Although data is seldom available as needed, modern data mining methods could aid in obtaining the necessary data for the model construction.

Model validation is a crucial aspect of any modeling; otherwise, its application to real-world problems could be misleading. In this sense, for future works, validation should always be considered and, if not possible, justified. While model validation helps guarantee the replicability of the model to real-life situations, optimizing the model structure helps the reduction of model complexity, which influences subjectivity when expert judgment is required to build the model. When the structure is optimized, modelers will spend less time with expert elicitation without losing the model's ability to provide helpful information.

Other topics, such as model translation into software, testing with other scenarios, cooperating with enterprises and testing with real systems, relate to model applicability and reproducibility. While models are helpful for decision-makers, their actual use can be tricky depending on their level of knowledge around programming and reading models' outputs. Therefore, producing some software that enables decision-makers to test different scenarios quickly and explore the multitude of outcomes of each model should break down barriers for model application. Moreover, stakeholders are generally only involved in specific parts of the modeling but not throughout the entire process, which leads to oversimplifications or generic models. If stakeholders and enterprises interested in the risk being analyzed through the models were included, models should become more consistent with practical needs.

Finally, global environmental and social climates are constantly

Table 4
Summary of future research recommendations to enhance the applications of BN in the energy sector.

Topic	Source
Dynamize the model	[30,49,57,106,111]
Use of continuous variables	[29]
Using data mining methods	[58,62]
More data	[61,91,54,138]
Validation of the model	[117]
Optimize model structure	[26]
Translation of model into software	[92,65]
Test with other scenarios	[74]
Cooperate with enterprises	[67]
Test with real systems	[99,126]
Integrate with climate models	[97]
Include economic and environmental factors	[32]

changing and intrinsically related to energy production and consumption. Therefore, holistically including other aspects of the social and environmental domain in BN models would bring new insights into the risks associated with developing energy systems and their components. Furthermore, climate change can impact the energy sector and energy markets everywhere, and interconnections between BN models and climate models are advisable to unravel new layers of risk within energy products.

6. Conclusions

This review examined BN applications in the energy sector, including production, use and distribution. The systematic review showed that using BN in risk analysis encompasses various objectives and is focused on different types of risk, such as leaks, cyber-attacks, failures, faults, oil spills, investments, structural health and others. Nonetheless, although the application areas were diverse, most BN models in the review were interested in technical assessments of oil & gas infrastructure risk, technical assessment of nuclear power plants risks or environmental risks of oil & gas deployment, with only a few studies covering socio-economic risks.

BN is an essential tool for the energy sector, for it can help decision-makers make informed decisions about energy investments, energy policy, and energy operations. BN can provide valuable insights into the trade-offs and risks involved in different decisions by allowing for the analysis of possible scenarios and the probabilities of different outcomes. BN can easily integrate multiple sources of data and knowledge about energy systems, such as historical data, simulations, expert opinions, and sensor readings. This helps to build a completer and more accurate model of the system and to identify cause-and-effect relationships.

However, the need for more transparency regarding using experts' judgments and validating the models has been highlighted to guarantee their ability to support real-world decision-making procedures. Moreover, it is suggested that social, environmental and economic aspects are included to provide a more holistic risk assessment in sustainability, especially when considering climate change prospects. Developing sound and robust BN based on state-of-the-art methods such as Deep Learning Models is another step toward more reliable models.

In conclusion, applying BNs in the energy sector can shift the context into more environmentally friendly energy options, assess their risk in an oil & gas-dominated sector, and bridge the gap between science and real-world applications.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Claudio Augusto Oller do Nascimento reports financial support was provided by Petronas Brasil.

Data availability

Data will be made available on request.

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