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Review

An assessment of probabilistic disaster in the oil and gas supply chain leveraging Bayesian belief network

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ABSTRACT

The oil and gas supply chain (OGSC) is considered to have one of the most significant stakes in the U.S. economy because of its interconnectedness with supply chains in other sectors, such as health and medicine, food, heavy manufacturing, and services. While oil and gas development is expanding exponentially, various factors ranging from man-made to natural disasters can hinder OGSC processes, which, in turn, can result in inefficient and costly operations in other sectors. This study presents a Bayesian Network (BN) model to predict and assess disasters in the OGSC based on seven main factors: *technical, economic, social, political, safety, environmental, and legal.* BBN is a probabilistic graphical model that is predominantly used in risk analysis to illustrate and assess probabilistic relationships among different variables. To draw meaningful managerial insights into the proposed model, sensitivity analysis and belief propagation are used. The results indicate that of the seven factors responsible for OGSC disasters, *technical* factors have the highest impact while *legal* and *political* factors have the lowest.

1. Introduction

Supply Chain Management (SCM) is a sequential group of activities that starts with the sourcing of raw materials, proceeds through manufacturing or assembly of a product or service, and ends with delivery to a consumer within a specific timeframe (Tan, 2001; Holmberg and Holmberg, 2012). In the oil and gas (O&G) sector, the supply chain involves exploration, production, refining, distribution, and retail (Barclays, 2015). SCM involves the design and management of seamless inter- and intra-organizational processes, and critical product, demand, information, and financial flows through the participating entities (Coyle et al., 2017). The ultimate goal of SCM is to maximize the value generated to end customers and to supply chain entities (Chopra and Meindl, 2016). To achieve these goals, SCM requires the collaborative effort of all functional areas responsible for supply chain activities, such as material sourcing, production, quality management, and end-customer delivery (Lee et al., 2017; Lambert, 2014; Maleki et al., 2013; Mentzer et al., 2001). Due to the number of functions involved in optimizing supply chain performance, sub-specialties span diverse fields including information technology (IT), risk management, financial management, logistics, and transportation. In the modern world, SCM plays an important strategic role in enterprise growth, not only for business organizations, but also for non-profit companies.

Unlike traditional management practices, SCM is a rapidly evolving field built on continuous advancements in computer and information technologies, such as artificial intelligence (AI). However, data and reports are still used to make critical decisions to minimize operational errors. In some cases, companies plan and execute supply chain strategies to minimize cost and increase profitability, yet face considerable financial losses each year. These losses stem from several issues, including environmental disasters, operational instability, political unrest, lack of organizational support, poor route selection, global financial breakdown, social and labor dissimilarities, accidents, and logistics mismanagement (Macdonald and Corsi, 2013; Ivanov et al., 2017; Sodhi, 2015). These issues are known as *supply chain disruptions (SCD)* and can inflict huge economic losses on both a company and a country. To develop a resilient supply chain network, the causes of disruptions must be known and thoroughly analyzed so that appropriate measures

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can be taken to mitigate potential losses.

The oil and gas supply chain (OGSC) is susceptible to a wide range of setbacks due to environmental, economic, technical, safety, legal, political, and social factors (Saad, 2014; Jiang et al., 2019; Ebrahimi et al., 2018). The U.S. oil and gas industry is a high risk operation that has experienced many challenges in the past. For instance, after the Global Financial Crisis (GFC) in the fiscal year 2008–2009, a hike in oil prices led to a decrease in overall GDP to 1.9%. Also, in 2016, oil exploration and extraction costs increased more significantly than other years (Thorbecke, 2019). Moreover, the lack of sustainable practices and technical difficulties have caused hardships for oil and gas refinery operations. For instance, in 1988, oil rig fires caused 167 deaths and a gas leakage at Amuay Oil refinery caused 39 deaths. Another incident in 2010 was the oil spill in the Gulf of Mexico that caused a severe explosion. These kinds of operational hazards have also caused habitat depletion, atmospheric emissions, surface water disruption, and increased labor stress (Barclays, 2015). Natural disasters have also affected the OGSC. In 2017, Hurricane Harvey caused severe flooding that resulted in the shutdown of many oil refineries near Houston on the gulf coast of Texas and at nearby ports that transported approximately six million barrels of oil each day. As a result, the price of oil sky rocketed to $100/barrel (Stanberry, 2009). In the early 2000s, the oil and gas supply chain faced schedule delays and cost overruns because of investment regulatory policies and geopolitical difficulties. Transporting commodities from the U.S. to other areas by pipeline, road, and barge was disrupted due to politically influenced investment policies, which imposed an operational limit of a maximum of 50% of total U.S. supply (Tan and Barton, 2017). These statistics clearly underscore the need to conduct research to develop a resilient oil and gas supply chain network that can withstand and minimize the disruptions cited above.

The objective of this study is to identify and quantify the salient factors that could generate an OGSC disaster in the U.S. and predict the overall disruption by developing a Bayesian network (BN) model. The model is based on an extensive review of the extant literature, followed by the expert judgment of relevant fields to identify the risks and uncertainties associated with the complexity of the OGSC network. This novel approach will help practitioners gain a better understanding of disruptions by presenting the facts, reasons, and effects of disruptions and the courses of action needed to develop a resilient OGSC network.

The remainder of the paper is structured as follows: Section 2 presents the literature review on the causes, effects, and predictive measures related to the OGSC as discussed by other researchers. Section 3 discusses the Bayesian Network approach. The 5-step methodology for the assessment of OGSC is proposed in Section 4, followed by a case study description of the factors and quantification techniques in Section 5. Section 6 presents advanced analyses, such as propagation and sensitivity analysis, to provide further insights germane to the underlying model. The paper concludes with the implications of the current study, its limitations, and avenues for further research.

2. Literature review

This section discusses the existing literature pertaining to OGSC disruptions, especially in the U.S., and presents numerous studies that attempt to analyze the OGSC network in order to reduce disasters stemming from adverse conditions and operational uncertainties.

Depending on the type of disruption and impact, researchers have made notable efforts in using theoretical, statistical, and economic analysis to provide evidence and guidance on solving disruptive issues. For example, Consiglio et al. (2006) employed a theoretical analysis technique named “Social Impact Assessments (SIAs)” to assess community and social circumstances affected by the O&G sector. In another study, Attanasi (1998) conducted a 3-year survey of oil and gas resources for both onshore and offshore reserves in the U.S., as well as the logistics activities for those reserves. The findings of this study indicated that the accumulation of resources may have significance for the OGSC depending on locational variations in demand and supply. In a related study, Stanberry (2009) delineated the trade deficit and import/export balance for petroleum as consequences of global trade policy that impact the supply chain for oil.

Lack of organizational management can lead to increased supply chain cost and hamper overall performance. Al-husain (2014) identified logistics areas, lead time, remote inventory, and the “swap” practice of oil and gas derivatives as some of the logistics challenges encountered by countries around the world. The economic effect on the O&G industry, not only depends on financial transactions, but also on employees’ sex, race, age, and ethnicity. A comprehensive study of employment and log wages in the oil and gas (O&G) industry concluded that men, primarily black and Hispanic, are engaged more after the booming of the oil and gas industry (Austvik, 2017).

In recent times, the sustainability of the O&G industry has experienced several downturns in the U.S., Canada, Australia, and even in Brazil, West Africa, and Asia. Primary and secondary data have revealed that large scale hydrocarbon leakage and system failures have caused dramatic disruptions in economic growth and resource management (Anis and Siddiqui, 2015). Similarly, after the shale revolution, U.S. stock prices and oil prices varied significantly. In a study conducted by Bernanke, it was found that oil price increases driven by supply (rather than demand) correlated positively with stock prices after the shale revolution, while the converse was true before the shale revolution (Thorbecke, 2019). The implication is that oil price shocks need to be dissected to understand how they might disrupt supply chains and affect the overall financial performance of companies heavily dependent on oil.

For the past two decades, researchers have used various mathematical approaches to address O&G supply chain problems, such as production and transmission delays. Some researchers attempted to use optimization techniques to analyze the subject. For instance, Zarei and Amin-Naseri (2019) presented minimization techniques for transporting gas, as well as the overall planning for its extraction, production, storage, and export. Along the same lines, Carrero-Parreño et al. (2019) used a mixed-integer linear programming (MILP) model to compute the reuse of flow-back water in onsite treatment plants where the water from shale gas wells deteriorated and caused an increase in cost to the operating system. Gao et al. (2017) also used MILP to solve process design challenges (extraction, transport of shale gas) and demonstrated the outcome as a sustainable process control mechanism and life cycle optimization. A number of research studies show that when using conventional O&G techniques, companies frequently face costly transactions, slow delivery, and customer dissatisfaction – factors that have direct implications for supply chain performance. For example, Montagna and Cafaro (2019) reported that horizontal and vertical hydraulic fracturing, slow extraction timing, machine parts maintenance, civil works, and equipment failure are primary reasons for imperfect supply chain processes. The authors applied an MILP approach by creating an optimization framework to integrate the planning of materials, supplies, economic budgeting, and capital expenditures to control these problems. To overcome logistics challenges, Joshi et al. (2017) presented a linear programming model to evaluate demand, capacity, and transportation costs associated with logistics optimization. Their proposed model analyzed transportation chains in other countries by considering environmental, socio-economic, and political effects.

In order to investigate demand, stock market, and price level, Nguyen and Okimoto (2019) developed a smooth transition vector autoregressive (STVAR) model to identify outcomes linked to price and location of the supply of O&G. The asymmetric relationship between price and the stock market was also found to cause other issues, particularly consumer takeovers, purchase reserve, and merger and acquisition (M&A) effects in the global O&G market. Cox and Ng (2016) implemented a distinct logistic regression analysis model to apply these factors to predict a long period of prognostication in oil and gas reserves, exchange deals, and global annual takeover. Different political ideologies and increased global warming have caused extreme events such as earthquakes, and have placed the oil and gas supply chain in a presumably dead zone. From statistical measures, Gray et al. (2019) summarized people's opinions about the impact of human activities on climate change. They also explained how man-made activities like stock market policies, political tension, price randomness, and frontier transit issues cause OGSC disruptions. A somewhat different approach was taken by Simpson (2012), who conducted a statistical analysis to investigate the economic and financial crisis in the oil and gas sectors of the U.S. Bouejla et al. (2014) and Mbamalu and Edeko (2004) utilized a Bayesian network approach to mitigate the issues pertaining to OGSC; however their study did not cover all possible aspects of OGSC disasters.

Another stream focuses on mitigating the disruption and enhancing sustainability of oil and gas supply chain network. For instances, Wan Nurul Karimah et al. (2006) proposed a Pacific Sustainability Index (PSI) and a benchmarking method to identify the qualitative patterns for inconsistent behavior in OGSC disruption based on environmental sustainability. The report shows that emissions, recycling, logistic outsourcing, and wastages are primary contributors for oil and gas disruption. In a recent study, Etokudoh et al. (2017) adopted Resource-Based Theory (RBT) and Network Theory (NT) in associating logistics deficiencies factors with OGSC risk. Gao and You (2018) performed integrated hybrid life cycle analysis (IHLCA) techniques to estimate cost for electricity generation, which plays a major part in shale gas operations, and supply chain. This quantification described the cost effect of different parameters on oil and supply chain process, distribution and risk prediction. Tang et al. (2018) assessed risk and resiliency level of offshore oil extraction unit. More specifically, they used a multivariate composite index to quantify fatalities, injuries, damage, asset management and prevention measures for OGSC disasters. In a similar vein, Tong et al. (2018) evaluated unconventional O&G resources throughout the world which dictate the overall supply chain risks in O&G sectors. In other related work, John et al. (2019) applied statistical methods on survey data to evaluate the disruptive factors in supply chain distribution network of Nigeria O&G sectors. Along the same lines, Ibrion et al. (2019) analyzed 15 case studies of various hazard, accidents and disasters in O&G sectors via Life Cycle Assessment (LCA) methods to evaluate disruptive situations.

A somewhat traditional yet effective approaches have been applied by some researchers to analyze and mitigate the OGSC disruption. Mandira et al. (2018) used Just in time (JIT), Kanban, TOC, Total Quality Management (TQM), and ABC analysis for total productive

Table 1
Current themes in O&G industry.

Authors	Approach	Application Area and Findings
Attanasi (1998)	A modified '"McKelvey box" used for classification and assessment	Evaluation of recoverable oil, both in onshore and state waters; also determining conventional resources of crude oil and natural gas.
Consiglio et al. (2006)	Questionnaires for Social Impact Assessment (SIA)	An insightful description of different social dimensions and their impacts on oil and gas industries.
Wan Nurul Karimah et al. (2006)	Pacific Sustainability Index (PSI) and benchmarking method	Evaluation of index factors from environment and social perspective for oil and gas supply chain disruption.
Simpson (2012)	Ordinary least squares regression	Evaluation of gas price index and volatility of the stock market based on political, social, and legal factors.
Al-husain (2014)	Inventory data in transportation and in-transit inventory	Evaluating asset swap practices and opportunities for swapping in logistics areas and remote inventory for the oil and gas industry.
Anis and Siddiqui (2015)	Theoretical evaluation with the empirical methodology for sustainability	Explains and illustrates sustainable development in economic, environmental, and social issues leading to analyzing threats in oil and gas companies.
Cox and Ng (2016)	Capital asset pricing model, regression analysis and Granger causality test	Assessment of market policies and decision making associated with natural gas price and corporate takeovers.
Etokudoh et al. (2017)	Resource-Based Theories (RBT) and Network Theories (NT) approach	A multicase, exploratory and qualitative approach is attempted to logistics outsourcing sustainability and risk assessment in Nigerian Oil and gas industries.
Gao et al. (2017)	Large-scale nonconvex mixed-integer nonlinear program (MINLP) model	Optimal design of SCM and decision criteria on drilling, fracturing plan, location, and length of pipeline in the O&G extraction plant.
Joshi et al. (2017)	Linear Programming Model	Optimization of transportation network in oil and gas SCM to reduce cost and uncertainty.
Gao and You (2018)	Integrated hybrid life cycle analysis (IHLCA)	Optimal cost estimation of electricity generation from both upstream and downstream shale gas supply by using LCA method
Mandira et al. (2018)	viz., JIT, Kanban, TOC, TQM, TPM and ABC analysis	Evaluation of value chain quickness of oil and gas supply chain in the UAE in understanding the risk resiliency during uncertain conditions
Shqairat and Sundarakani (2018)	questionnaire based survey and statistical analysis	Evaluation of value chain quickness of oil and gas supply chain in the UAE understanding the risk resiliency during uncertain conditions
Tang et al. (2018)	Composite index development method	Assessment of performance, risk level, and resilience by evaluating composite index in order to address major safety in offshore oil extraction units
Tong et al. (2018)	Volumetric analogy method and Monte-Carlo simulation	An overview of undiscovered recoverable oil and gas reserves throughout the world by using an evaluation method
Atris and Goto (2019)	Data envelopment analysis (DEA) and the Kruskal-Wallis rank sum test	Evaluation of unified efficiency by considering environmental (carbon emission footprints) and operational (assets, revenue and exploration) efficiency to mitigate risk factors
Benjamin J. Gray et al. (2019)	Ordinary Least Squares and binary logistic regression	Estimation of global warming and induced seismicity based on public opinions of weather patterns in the Oklahoma oil plant.
Carrero-Parreño et al. (2019)	Mixed-Integer Linear Programming (MILP)	Increasing total benefits and reducing total costs of shale gas water management.
John et al. (2019)	Statistical analysis from survey data	Determining critical factors to disrupt supply chain downstream process for petroleum based oil and gas industry
Montagna and Cafaro (2019)	Mixed integer linear programming (MILP) model	A novel optimization framework that combines service provision and material supply in the development of unconventional and conventional supply chain networks.
Nguyen and Okimoto (2019)	Smooth transition vector autoregressive (STVAR)	Demonstrates the relationship impact between natural gas price and stock market price of O&G industries.
Stanberry, 2009	Statistical and survey data	Decision on increasing oil export to minimize deficit based on trade agreements.
Thorbecke (2019)	Multivariate regression model	Established relationship among financial hedging, operational hedging, and commodity price exposure in O&G supply chain.
Zarei & Amin-Naseri (2019)	Mixed Integer Linear programming Model (MILP)	Calculation of minimum cost of production and transportation in OGSC
Rentizelas et al. (2020)	Survey method and institutional theory	Evaluation of major factors for sustainability of oil and gas supply chain in the Oman
Ibrion et al. (2019)	Life Cycle perspective Analysis	Identify the stages linked to oil and gas disasters through life cycle perspective and their main technical causes.

maintenance (TPM) and Total quality management (TQM) in drilling with emphasis on resource allocation and flow management to ensure seamless operation of OGSC. By the same token, Shqairat and Sundarakani (2018) performed statistical analysis in order to assess the critical factors for O&G disruption and ways to mitigate disruption. The different research studies and current themes of OGSC are summarized in Table 1.

For the last several decades, the OGSC has influenced the activities in many business areas, specifically, manufacturing and service industries, transportation, healthcare, and financial institutions. Therefore, risk events that lead to disruptions in the OGSC can have a huge direct and indirect economic consequences for such business areas. Higher oil prices due to shortages in supply following disasters can raise the cost of production and delivery of goods, trigger job losses, and reduce returns to investors. For example, damage to refineries caused by Hurricane Katrina in 2005 resulted in an immediate spike in the price of oil futures, requiring the government to release 30 million gallons of oil from the US Strategic Petroleum Reserve to stabilize prices (Pan, 2005). As climate change becomes a growing reality, the threat of severe weather implications on the OGSC cannot be overlooked in the future. In 2013, the extraction, pipeline, and refining operations in the O&G sector in Louisiana was estimated at $5.9 billion or just over 7% of the state's wages (Dahi-Taleghani and Tyagi, 2015). Any disruption that impacts O&G operations, could have a direct impact on job losses and, consequently, household income. In the past decade, the oil and gas sector has struggled to deliver investor returns that parallel performance in previous decades due to many factors, including an increase in the leverage ratio in the O&G sector following the 2008 financial crisis (Ashraf et al., 2020). From these figures, it is evident that the O&G sector is sensitive to disruptions and any risk events in the OGSC can have significant financial implications in terms of lost revenues, profitability, legal fees, punitive damages, and environmental and social sustainability costs. Given this situation, the O&G sector would benefit tremendously from the use of practical quantitative methods to identify and characterize the salient factors that contribute to supply chain disruptions so that more effective risk mitigation methods can be developed in the future. Yet, despite the ubiquitous use of oil and gas to support economic activity, few methods are exist to identify and organize the salient factors that lead to disruptions. Moreover, the literature lacks methods to quantify the probability of a disruption in the O&G sector. Rather than identify the risks in isolation, the industry could benefit from having a more holistic structure that delineates the critical risks to support better risk mitigation planning in the OGSC.

Of the different research models used in the last few years, the BN model is highly accessible, and its application has spread to e-commerce, marketing, domestic energy supply, transportation, social media, and many other sectors. The BN model can be applied to predict end-user integration, profit/loss, future investments, and customer satisfaction, banking, finance, and even environmental risk. The BN model, which is a widely used methodology among researchers, provides a unique analytical approach that helps to understand probabilistic functions in need-based variables. Considering risk as two-fold (likelihood and outcome), the BN method provides subjective belief propagation based on past supplier performance, disruption events, disaster history, and financial factors. Moreover, the BN provides significant help in predicting interventions, handling missing data, and avoiding overfitting data. Readers who are interested in additional information on BNs are referred to the works of Lockamy III and McCormack (2010); Maleki et al. (2013); Shahan and Seepersad (2012); Sharma & Kumar Sharma and Sharma (2015); and Abolghasemi et al. (2015). Readers who desire a more profound treatment of the various applications of the Bayesian Network across different domains are directed to the works of Amundson et al. (2012)), Lawrence et al. (2020), Hossain et al. (2019a, 2019b, 2019c, 2019d) (supply chain), Hossain et al. (2019a, 2019b, 2019c, 2019d) (waterway port), (electrical infrastructure), Song et al. (2013), Yet et al. (2016) (project management), Arizmendi et al. (2012) (data classification), Han et al. (2012) (system of systems) Hänninen et al. (2014), (traffic accidents), Hossain et al. (2020a, 2020b) (smart grid) (port and supply chain interdependencies), Saini (2008) (power system), and many more.

It is apparent from the review of the literature that there is lack of research that considers the predictive approach to assess the disaster of OGSC. To address this gap, this research adopted Bayesian network as a probabilistic approach in the OGSC network to capture all the causes of OGSC failure that predict disruptions of the network. The following are contributions resulting from this study:

- Identification of factors that are responsible for the disruption of the OGSC network.
- Development of a comprehensive BN model that captures all the causal relationships among the different factors that predict OGSC disruption. This model would help to develop strategic plans and recommendations to manage the uncertainty and damage related to the OGSC network.
- Use of a set of advanced analyses, such as belief propagation and sensitivity analysis, to provide better insights into the resilience of the OGSC network.
- Demonstration of the extensibility of the BN as an efficacious tool in navigating and offsetting supply chain and logistics management problems.

This research strives to support practitioners in developing and understanding the robust network model pertaining to OGSC disruptions.

3. Theory of Bayesian Network

In this section, we present the fundamentals of the Bayesian Network (BN), a directed acyclic graph (DAG) used for statistical extrapolation by establishing probabilistic relationships among nodes (interacting variables) and edges (arcs).

An illustration of the BN is provided in Fig. 1 through a scenario related to the current research problem. If we consider, psychological effect and cultural & social infrastructure impact are two main subfactors of the social factors related to OGSC disruption. In other words, the posterior probability of social factor is conditioned upon two subfactors Psychological effect (S1) and cultural & social infrastructure impact (S2), respectively. On the other hand, the probability of overall oil and gas disruption is also dependent upon the probability of the social factors related to OGSC disruption. From a Bayesian theory perspective, S1 and S2 are the parent nodes of S3, and so S3 is the child of S1 and S2. Similarly, S4 is the child node of S3 and conversely, S3 is the parent node of the S4. All these nodes are connected through edges based on cause-and-effect relationships.

The relationships between the variables correspond to states that provide probabilistic values associated with earlier nodes. The general expression of the full joint probability distribution can be represented using the following equation (1):

$$P(S_1, S_2, S\ldots, S_n) = P(S_1|S_2, S, \ldots, S_n)P(S_2|S_3, \ldots, S_n)\ldots P\left(S_{n-1}|S_n)P(S_n) = \prod_{i=1}^{n} P(S_i|Parents(S_i)\right) \tag{1}$$

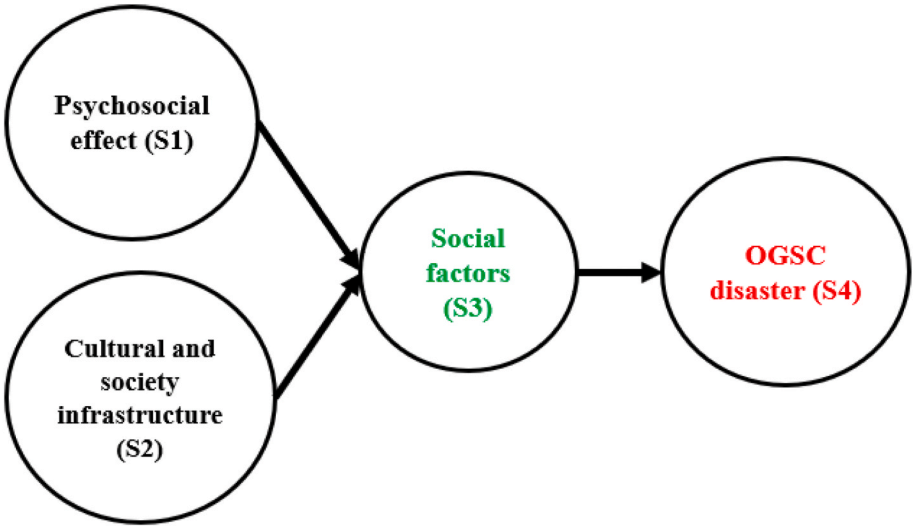

Fig. 1. An illustration of a Bayesian Network (BN) with four variables.

4. Proposed model

4.1. Methodology of the proposed framework

The methodology for the proposed framework was established through an organized review of the extant literature. The search for the relevant literature was narrowed using the Scopus database and relevant keywords (i.e., *supply chain disaster, supply chain risk, supply chain disruption, supply chain resilience, oil and gas supply chain)* that are germane to supply chain disaster. The database search included published, peer-reviewed, and proceedings papers that covered all aspects related to the O&G supply chain system and its network performance. Initial search results produced 100+ papers and further screening was carried out based on the suitability and pertinence of the subject. To further narrow the search pool, a more focused list of papers was selected that related only to oil and gas supply chain disasters with logical explanations for causes and consequences of disruptions that occur in the oil and gas supply chain. As a result, a total of 65 papers were selected for final review of theoretical and analytical considerations.

This review helped to determine the areas of supply chain functionality and led to the creation of an underlying Bayesian Network model pertaining to OGSC disasters. Fig. 2 illustrates the steps followed to develop the research methodology.

4.2. Proposed 5-phase interdependency disruption assessment process

This section describes the proposed O&G disruption assessment process of our study. To properly evaluate the disruption of the O&G supply chain, it is imperative that the main variables (factors) involved in disruption are identified. These factors were derived by employing the following steps: First, a detailed literature review was conducted and seven major factors implicated in OGSC disruptions were identified in conjunction with expert opinion. Second, sub-factor parameters belonging to each major factor in OGSC disruption were determined based on qualitative and quantitative measures, including recent statistics, historical data, the frequentist approach, and expert opinion. Finally, the variables were connected in a logical manner to develop the underlying BN model.

Further advanced analyses, such as belief propagation and sensitivity analysis, were conducted to draw insights into the causes, consequences, and countermeasures of OGSC disruption and to affirm the authenticity of our underlying model based on the collected data. The 5-phase disruption assessment process is discussed below and depicted in Fig. 2. The base Bayesian Network (BN) model is illustrated in Fig. 3 using the *AgenaRisk* software.

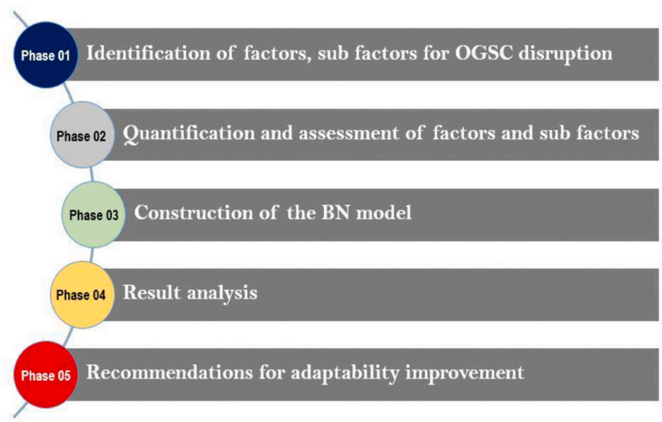

Fig. 2. Proposed 5-Phase Assessment process.

- **Phase I** (Identification of factors and subfactors in OGSC disruption): In this phase, we identified the possible factors and sub-factors associated with disruptions in the OGSC. Next, expert opinion was sought to finalize the salient and less important factors and to eliminate the irrelevant factors.
- **Phase II** (Quantification and assessment of factors and sub-factors): The second phase was to quantify the selected factors and subfactors. This included a determination of the likelihood of the event occurring based on a subjective or frequentist approach.
- **Phase III** (Construction of the BN model): The quantified data was fed into the BN model and simulated to assess the likelihood of disruption in the OGSC.
- **Phase IV** (Results analysis): A set of advanced analyses, such as belief propagation analysis and sensitivity analysis, were conducted to draw insights into the fundamental model.
- **Phase V** (Recommendations for adaptability improvement): In the last phase, recommendations were made to enhance OGSC performance based on conclusions derived from a technical analysis.

5. Problem description and model formulation

This section uses a case study to discuss the problem and model

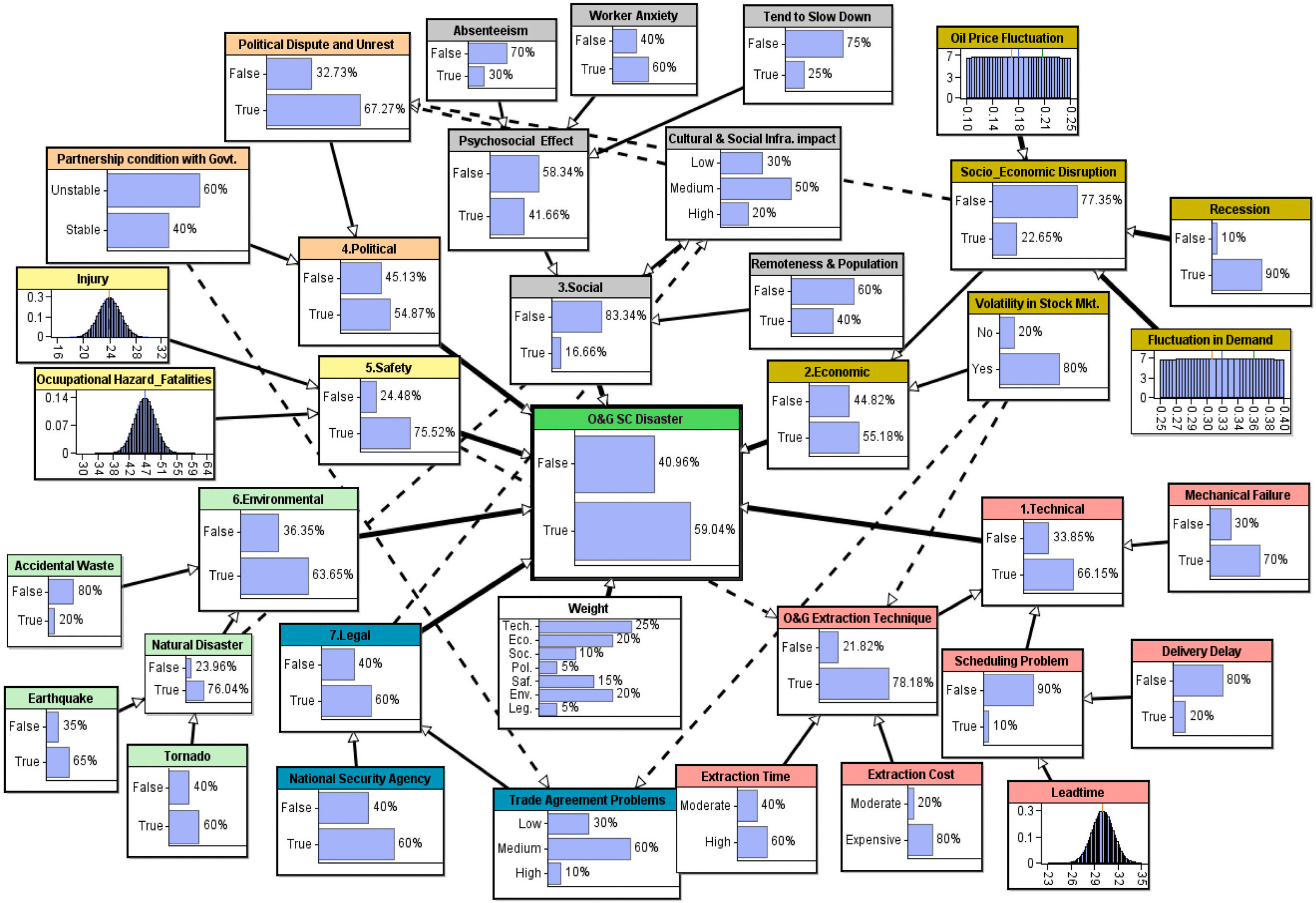

Fig. 3. Base BN model for measuring the overall disruption of the OGSC network.

formulation.

5.1. Case study description

In this study, we chose the U.S. oil and gas supply chain (OGSC) as our primary case study because the OGSC is essential to the U.S. economy. Each year the U.S. earns around 8% of its revenue from the nation's oil and gas domestic products. Currently, around 10.3 million jobs are directly and indirectly linked to the O&G industry. OGSCs face several threats due to different risks throughout the year. Because of its importance to the U.S. economy, oil and gas commodities and their supply chain processes need to be thoroughly assessed with a view to minimizing unwanted losses. Using a case study as background, this research will evaluate and prioritize risk factors and find suitable improvements to considerably lessen the effects of disruption in the U.S. oil and gas supply chain.

5.2. Description of the factor and quantifications

In this section, we present different factors and sub-factors responsible for OGSC disruptions. Table 2 summarizes the main factors and subfactors related to OGSC disasters derived from the supply chain network literature.

5.2.1. Technical factors

- *Mechanical failure:* Unexpected mechanical failure of tools and instruments used in oil extraction, maintenance, and overhaul require immediate attention to prevent financial losses. When overhaul problems, such as repair, replacement, or installation of extraction machine components take long periods of time, the delivery of refined oil and gas may be delayed. Frequently, O&G companies require lengthy periods to address overhaul issues due to the unavailability of machine parts and/or maintenance workers. (HEI, S2015).
- *Oil and gas extraction techniques*: In the U.S., there are more than 130,000 active oil and gas extraction sites, including some critical areas like the Southwestern Permian Basin, the Gulf of Mexico, the Eagle Ford Basin in Texas, Bakken oil fields in North Dakota, and Colorado's Niobrara shale gas site, where both workers and machines are continueously extracting oil and gas. These locations vary in the type of extraction techniques employed based on site, budget, volume, depth of oil fields, and technical support (Ebrahimi et al., 2018). According to the literature, there are two sub-factors related to oil and gas extraction techniques that might have an adverse effect on the performance of the OGSC.

High extraction time (delay): O&G extraction sectors are highly sensitive and risky ventures. Technical design risks, settlement risks, and management risks are time-sensitive; yet, minimizing these risks entail lengthy procedures that require efficient workers. Supply chain integration (SCI) techniques allow operational activities and extraction processes to run smoothly, preventing extraction delays that might have a negative impact on OGSC performance (Ebrahimi et al., 2018).

Overwhelming extraction costs: According to the national assessment of U.S. oil and gas reserve data, approximately 960,000 oil fields are operational, resulting in production of 2.5 BBO (billion barrels of oil) (Attanasi, 1998). As of 2019, U.S. oil field production has increased to 12,232 thousand barrels per day or 4.5 billion barrels of oil per year (U. S. EIA).

Given the huge quantity of oil extracted, it is clear that the operation of O&G processes will influence extraction costs. More expensive tools and faster more efficient operations will ultimately improve technical performance of the overall OGSC.

- *Scheduling problems*: Both oil extraction and shale gas extraction suffer from work scheduling disruptions due to inconveniences that arise from geological shale formation. Any failures or inconsistencies in the drilling and hydraulic fracturing operations of the extraction process can lead to delays. The risks associated with failure also hamper routing, storage, and exports to end-users (Guerra et al., 2019; Zarei and Amin-Naseri, 2019). It seems that the OGSC process can be significantly disrupted due to long lead times and slow responsiveness at the extraction point.

Lead time to supply oil: In recent years, oil and gas extraction companies and their associated corporate giants used new technologies and increased their production rates significantly. However, scheduling capabilities have not kept pace with the increase in production. Consequently, the methods applied have been inadequate to meet new time-imposed demands of customers. Lead time delays encountered in pipeline monitoring systems, refining quality, product transfer to consumers, commodity transfer, and upstream to downstream activities have all had detrimental effects on the OGSC.

Delivery Delay: The responsiveness of the supply chain depends primarily on timely execution of all supply chain activities, such as order cycle, customer service, outsourcing, and just in time (JIT) production and delivery. In the OGSC, firms focus on improving key areas like dynamic capabilities, strategic relationships between customers and suppliers, reliability, planning and control systems, and development of oil processing plants to increase SC performance levels (Saad, 2014). Inefficient responsiveness leads to poor supply chain processes for oil and gas industries and a delivery delay that could result in huge financial losses.

Table 2
Existing threads in OGSC disruptions.

Criteria	Sub Criteria	References
Technical	• Mechanical failure • Oil and gas extraction techniques • Scheduling problems	• Saad (2014), López-Díaz et al. (2018), Li et al. (2017), HEI Special Scientific Committee (2015). • Washington Post, Ebrahimi et al. (2018), Attanasi (1998). • Guerra et al. (2019), Zarei and Amin-Naseri (2019), Gao et al. (2017).
Economic	• Socio-economic disruptions • Volatility in stock market	• Anis and Siddiqui (2015), Nguyen and Okimoto (2019), Rickman and Wang (2019), Stanberry and Aven (2019). • Al-husain (2014), Cox and Ng (2016), Thorbecke (2019), Simpson (2012).
Environmental	• Natural disasters • Accidental waste release	• Barclays (2015), Gray et al. (2019), Souders et al. (2005). • Gao and You (2018), Kbah et al. (2016), Policies, Petroleum (1966).
Safety	• Injury • Occupational hazards and fatalities	• Tang et al. (2018), Barclays (2015). • Mortality Weekly Report (2013), Attanasi (1998), Thorbecke (2019).
Social	• Cultural and social infrastructure • Remoteness and population density • Social and psychosocial effects	• Consiglio et al. (2006), Kardel (2018). • Rickman and Wang (2019). • Guerra et al. (2019), López-Díaz et al. (2018).
Legal	• National security anxiety • Trade agreement problems	• Walde (2008), Jiang et al. (2019). • Stanberry and Aven (2019), Simpson (2012)
Political	• Unstable partnerships & investments with government • Political disputes and unrest	• Kardel (2018), Tan and Barton (2017). • Gray et al. (2019).

The modeling procedure of the *technical factors* is discussed below:

To model the technical factors and sub-factors, two types of variables were used*: Boolean variables* and *continuous variables*. Boolean variables are expressed using a dichotomous response (true/false, yes/no) to represent positive and negative outcomes respectively. The false state describes a negative outcome, and the true state represents a positive outcome. Boolean variables were used to model *extraction time, extraction cost, delivery delay,* and *mechanical failure*. For instance, Fig. 3 illustrates that the probability of delivery delay is 20% *true* and 80% *false*.

$$Technical\ factor = NoisyOR\ (O\&G\ extraction,\ 0.50, scheduling\ problem,\ 0.50,\ mechanical\ failure\ 0.50,\ 0.10) \tag{5}$$

In other words, we assume that delivery delay happens 20% of the time (true state) and doesn't happen 80% of the time (false state). Similar logic has been applied to the other factors.

The truncated normal distribution is found to be the most appropriate distribution to model continuous variables such as *lead time*. It is a modified normal distribution that is defined using four parameters: μ, mean (i.e., central tendency), σ^2, variance (i.e., confidence in the results), and upper and lower bounds. For example, based on historical data, the lead time to supply oil generally varies from 20 to 35 days with an average of 30 days. It is also obvious that lead time cannot be negative. Thus, a truncated normal distribution is suitable for defining the upper and lower bounds for the *lead time* random variable.

Fig. 3 shows that the *technical* factor is conditioned upon three sub-factors: *mechanical failure*, *O&G extraction techniques,* and *scheduling problems*. Other hidden or unknown factors could also contribute to the *technical* factor. To improve the accuracy of the model and the posterior probability of the *technical* factor node, the *NoisyOR* function can be applied. The *NoisyOR* function is an easy way to model uncertain relationships in a Bayesian network and compensate for absent (leak) factors that could contribute to a *true* outcome. Generally, a NoisyOR function consists of a non-deterministic line failure function with inputs that result in a boolean output. If a line failure event occurs (i.e., is *true*), a false output will be obtained regardless of the input. The probability associated with the line failure is called an "inhibitor probability". As an example, if $U_1, U_2, U_3, \ldots \ldots U_n$ are inputs that produce an output X, then a non-deterministic line failure N_i will result in Boolean outputs $U'_1, U'_2, U'_3, \ldots \ldots U'_n$. On the other hand, if a line failure event is *false*, the output will be equal to the input and the associated probability for the event will be calculated as (1 – inhibitor probability) (Srinivas, 1993; Vomlel, 2015). The logic is that a *NoisyOR* model will begin with a non-deterministic model, *F*, and failures will be introduced into the inputs until a more realistic model that incorporates only a few probabilistic parameters is achieved. The generalized model adds proximate deterministic values that assume the value will be "True" if the parent node is "True". Thus the "leak" node fulfils the missing values. Applied to the OGSC, the *NoisyOR* function will adjust for missing elements that could potentially affect post-disaster strategies.

For example, if there are some factors such *as* $C_1, C_2, C_3 \ldots C_n$ that are inputs in a conditional probability formula, then the event D is true only if C_1 is true while others are false. The conditional probability distribution $P(D|C_1, C_2, C_3 \ldots C_n)$ is computed from the input probabilities. Here, the *NoisyOR* function is useful and it is presented for each factor C_i,

$$M_i = P\left(D = True \middle| C_i = True,\ C_j = False;\ \forall_j \neq i\right) \tag{2}$$

where, M_i is the conditional probability being *true* if only the causal factor is true and all other factors are *false*. The function is written as follows:

$$NoisyOR\ (C_1, M_1, C_2, M_2, C_3, M_3 \ldots C_n, M_n, l) \tag{3}$$

Here, l is the leak factor representing the missing parameters in the model that contribute to the outcome being *true.* The conditional probability for event D being *true* can be described as follows:

$$P\left(D = True|\mathrm{C1}, \mathrm{C2}, \mathrm{C3}, \ldots ..\mathrm{Cn}\right) = 1 - \prod_{i=1}^{n}\left[(1 - p(D = True|C_i = True)(1 - p(l))\right] \tag{4}$$

The modeling equation of economic factors is presented in the following equation (7):

Equation (7) explains the probability of *O&G extraction*, *scheduling problems*, and *mechanical failure* using the *NoisyOR* function, where each of the included factors is assumed to be *true* while others are assumed to be *false.* The probability distribution is defined as 0.50 for each factor, i. e., these three factors will have similar effects on the *technical* factor. The probability distribution for hidden factor is 10%.

5.2.2. Economic factors

Socio-economic effects and *stock market price volatility* are the main issues for the economic disruption of O&G sectors. When the natural gas market faces a shock in U.S. demand, supply market prices and economic activities adjust upward or downward in response. Operational and financial hedging can be executed to mitigate the financial risk associated with median exposure states, commodity price randomness, and annual risk exposure.

- *Socio-economic disruptions*: Anis and Siddiqui (2015) stated that the "Triple Bottom Line" or TBL consists of environmental, economic, and social threats. These threats can impact the OGSC. Recessions can also cause socio-economic disorder in the OGSC.

Fluctuation in international oil price: An empirical investigation using a recession market scenario explained a large range of price fluctuations based on commodity control variables such as size, leverage, liquidity, and growth opportunities (Nguyen and Okimoto, 2019). These changes were found to accelerate during times of internal socio-economic disorder.

Recession: According to a case study reviewing boom and bust phases in the oil industry, an unexpected drop in mining employment escalated a recession in fiscal years 2008–2010, particularly in Louisiana, North Dakota, Oklahoma, and Wyoming (Rickman and Wang, 2019). Unemployment spikes similar to the one in this case study show how a recession could cause disarray in an OGSC network since there would be fewer workers in huge sectors.

Fluctuating demand in consumption: While exports of U.S. oil are expected to grow steadily over the next few years, exporting of refined crude oil is likely to suffer a decline in demand in the future as sustainable issues and carbon taxes force consumers to use renewable energy sources (Stanberry and Aven, 2019). Nonetheless, with a projected demand of more than 3 billion BBO annually, the potential for significant disruption in the OGSC in the U.S. still exists.

- *Volatility in the stock market*: The stock market reacts to supply chain complexities involving inventory and transportation components like railroads, tankers, and small vessels, with resultant randomness in stock prices (Al-husain, 2014). In the U.S., the oil and petrochemical industries often face stock price variations and market volatility which in turn result in negative consequences to the OGSC.

The modeling procedure of the *economic factors* is explained below:

As illustrated in Fig. 3, the *economic* factor consists of two factors: *socio-economic* factors and the *volatility of the stock market*. The following table (Table 3) describes modeling of the *economic* factor and its sub-factors.

The modeling equation for *economic* factors is presented in equation (6):

$$Economic\ factor = NoisyOR\ (Socio\ Economic,\ 0.75, Volatility\ in\ stock\ market,\ 0.50,\ 0.10) \quad (6)$$

5.2.3. Social factors

Because oil and gas producers (OGP) have an impact on social dimensions, in depth knowledge of worker migration, security, safety, wages and salaries, health, and social position is necessary (Consiglio et al., 2006). Screening of workers' skills, mental condition, work satisfaction, and monitoring of workers' social life is important. This type of assessment helps to identify social factors that disrupt SC activities in the oil and gas sectors.

- *Cultural and social infrastructure impact*: Government and private owners need to maintain a legal framework for employees and others to define cultural boundaries, norms, social status, position, healthy lifestyle, justice, and equity for the society as a whole, while also reducing corruption in O&G operations (Kardel, 2018).
- *Remoteness and population density* (*obstruction in remote areas)*: Although in general a social lifestyle associated with remoteness, low population density, work availability, and salary structure impact financial results, in reality the population density of remote areas can have a negative effect on supply chain processes (Rickman and Wang, 2019). Depending on the remote area population density, supply chain processes might be affected by increased safety issues due to transaction speed and efficiency requirements (Rickman and Wang, 2019).
- *Social and psychosocial effects*: When creating a new production facility or transferring facilities to an oil extraction site, there is some risk involved in habitat depletion, fragmentation, and degradation (Barclays, 2015). With regard to transfer of oil and gas commodities, social and psychosocial factors could result in OGSC disruption due to absenteeism, anxiety, and work preferences.

Absenteeism at work: Issues of absenteeism are a challenge for oil and gas producers in the supply chain. Public nuisances such as noise, vibration, and dust in the O&G work area (Barclays, 2015), may cause harmful psychosocial issues, leading to absenteeism in the workplace. An understanding of these issues is gained by examining worker profile, workplace safety measures, and employees' beliefs about the workplace (Guerra et al. (2019).

Worker anxiety: In the workplace, people often suffer from anxiety, especially in the O&G industry due to long term physical stress while operating machines, lifting heavy objects, and transporting oil manually (Kardel, 2018). Anxiety levels can help to explain workers' motivation, work safety, satisfaction, and stress level. Increase in worker anxiety can cause significant schedule delays and considerable workflow losses.

Workers tend to work slowly: Similar to the factors mentioned above, laborers and people can have work delay problems in handling the operations of the oil extraction process due to excessive work stress.

The modeling of *social factors* is summarized below:

Boolean logic was applied to the majority of the nodes contributing to social factors except the *cultural and social infrastructure* node for which the *Ranked Nodes Method* was used. *The Ranked Nodes Method (RNM)* uses an ordinal scale (i.e. good, medium, and bad) to express different states (Fenton et al., 2007). This scale is originally mapped based on Normal Distribution truncated values between 0 and 1. For example, as illustrated in Fig. 3, the probability of substandard *cultural and social infrastructure* is assumed to be 20% high, 50% medium, and 30% low based on historical data.

The modeling equation for social factors is designed using a comparative expression. It is assumed that if the *psychosocial effect* is higher than 35%, the *cultural and social infrastructure* is equal to or higher than "medium", and *remoteness and population density* exceed 40%, then the combined effect will cause social concerns for the OGSC.

5.2.4. Political factors

Government rules, regulations, and political involvement can have detrimental effects on the OGSC. Because of the significant investment and geopolitical issues involved in the O&G sector, corporate firms often negotiate with governments to have exclusive rights to supply oil and gas to end-users (Kardel, 2018). Since these decisions are relevant to the supply chain, they could have a major effect on the OGSC.

- *Partnerships & investment conditions with governments:* Decision-makers of O&G industries is trying to control future logistic expenses to meet expected demand. The owners of natural gas, crude oil, and shale gas and their corporate legislators offer a sustainable market for future energy sectors (Tan and Barton, 2017). However, poor political decisions can play a role in diminishing the performance of the O&G supply chain.
- *Political dispute and unrest*: Lobbying for oil and gas extraction has caused political disputes during energy crisis interventions. Moreover, in the past, decision makers and legislators have handled these disputes poorly, with negative consequences on O&G production and delivery. When protestors gain power through local and organizational turmoil, political decisions could bring supply chain operations to a halt.

The modeling of *political factors* is described below:

The factors contributing to political risk are represented in Boolean mode. For example, the political dispute and unrest node shows that

Table 3
Node Probability Table (NPT) for the variables describing the node economic factor and its contributors.

Variable Name	Modeling Technique	Modeling Description
Oil price Fluctuation	TNORM	Oil price is defined by truncated normal distribution with 17.08% mean fluctuation over the past 5 years (UCOP, 2020).
Fluctuation in demand	TNORM	The market demand for oil and gas is approximated using truncated normal distribution with an average of 32.84% fluctuation in past 5 years (UCOP, 2020).
Recession	Boolean	It is assumed that 90% of the time, a recession in the O&G market causes socio-economic disruption.
Volatility in the stock market	Boolean	Based on historical data, it is observed that 80% of the time, the volatility of the stock market contributes to creating an economic occurrence that leads to OGSC disruption, while 20% of the time, this might not happen.
Socio-Economic	Comparative expression	The OGSC socio-economic situation is conditioned upon three factors. If the values of oil price and market demand are higher than 17.08% (mean) and 32.84% (mean) respectively, and the likelihood of a recession occurring is higher than 75%, then there is concern about the socio-economic situation of the OGSC network (state of true), otherwise not (state of false).

there is a 75% chance that political disputes and unrest might result in occurrences that adversely impact the performance of the OGSC network, while there is a 25% chance that it might not happen. On the other hand, there is a 40% likelihood that unstable partnership conditions with the government could increase OGSC disruption. In this case, the *NoisyOR* function is used to express the political factor as shown in the following equation (7):

$$Political\ factor = NoisyOR\ (Political\ Dispute\ \&\ Unrest,\ 0.50, partnership\ condition\ with\ goverment,\ 0.50,\ 0.15) \quad (7)$$

5.2.5. Safety factors

Safety issues could lead to supply chain disruptions for any product. While environmental calamities could impede regular transportation of goods, man-made disasters such as occupational hazards, psychosocial risks, and accidents in manufacturing plants could impact lifestyle and cause persistent damage. Supply chain disruptions may be exacerbated by occupational injury and industrial hazards.

- *Injury*: Both O&G extraction sites and surrounding areas can result in injury due to natural hazards, atmospheric emissions, habitat depletion, rehabilitation, and restoration. These injury issues may cause unwanted disturbances in the OGSC (Barclays, 2015).

Injury by moving harmful materials: Many accidental events occur when moving harmful materials within the work site area, resulting in worker dissatisfaction and work stoppage until the problem is solved.

Handling bulk storage: Likewise, handling bulk volumes manually can also cause many accidents and impede production processes at O&G extraction sites, resulting in a loss for oil and gas producers.

- *Occupational hazards and fatalities*: Safety factors in the supply chain are one of the most important aspects to consider in conceptual workplace design. In-depth management of safety and safety measures are needed to reduce psychological factors, fatalities, and hazards (Mortality Weekly Report, 2013). Failure to evaluate safety measures could result in disruptions in the OGSC.

The modeling of *safety factors* is illustrated below:

As discussed above, the *safety* factor is concerned with two main contributors: 1) injury and 2) occupational hazards and fatalities. These two continuous variables are modeled using a truncated normal distribution (TNORM). The truncated normal distribution is characterized by a finite range (i.e., lower and upper bound); mean, μ (i.e., central tendency); and variance, σ^2. The modeling procedure for the *safety* factor and its contributors are presented in the following Table 4.

5.2.6. Environmental factors

Environmental impacts occur primarily in three domains, i.e., water, land, and air. Barclays (2015) discussed the contamination of water by pollutants and toxic ingredients from drilling and mining. Both natural and man-made disasters have the potential to cause supply chain disarray. Earthquakes, tornadoes, and accidental waste release can all cause inefficiency and disruption in the OGSC.

- *Natural Disasters*: Over the last several decades, the U.S. has faced many natural disasters such as earthquakes, forest fires, heavy rainfall, tornadoes, and other natural calamities. Below are two natural disasters that can impact the OGSC network.

Earthquakes (land): Due to land clearance for oil and gas extraction, a survey indicated that underground drilling and cutting could trigger earthquakes. This type of calamity could cause land deformation and road damage, thereby destroying supply chain transportation connections and slowing down the transfer of oil and gas.

Tornadoes (air and water borne): Tornadoes, which can be both air- and water-borne, have the potential to severely delay supply chain activities by causing the lockdown of industrial facilities and blockage of transit routes used for inland transportation of oil. Moreover, tornadoes could result in the worst case scenario of pipeline leakage and water contamination in the supply and distribution of refined oil products.

- *Accidental waste release*: Accidental waste release can cause major problems in distribution. Souders et al. (2005) mentioned that atmospheric emissions like pollutants, specks of dust, and waste disposal at extraction sites have caused suppliers to relocate their raw materials, products, and accessories to other areas. These man-made activities can lead to increased supply chain-related costs for the O&G industry.

The modeling process of *environmental factors* is described as follows:

Based on the expert judgment of practioners and scholars who are knowledgeable of the locations in which oil and gas operations are performed and the potential for earthquake disruptions in these areas, the prior distribution of the *earthquake* variable is subjectively defined with two states: *True* = 65% and *False* = 35%. This means that there is a 65% probability that an earthquake could cause an OGSC disaster. The same Boolean logic is applied to the *tornado* and *accidental* waste variables. Apart from these factors, some other hidden environmental factors could be responsible for OGSC disasters; therefore, the NoisyOR function is applied to design the environmental factor's node as presented in the below equation (8):

$$Environmental\ factors = NoisyOR\ (Accidental\ waste,\ 0.30, natural\ disaster, 0.75,\ 0.10) \quad (8)$$

5.2.7. Legal factors

Legal proceedings and political disputes of governments raise many questions about the extent to which oil and gas suppliers should be controlled. Foreign investors often circumvent legal proceedings by using cunning legislators. The result is that corporate suppliers may fail to meet fair policy requirements, thereby exposing themselves to negative consequences (Walde, 2008). The exposure explains some critical effects in the OGSC.

- *National security anxiety*: Political decisions regarding the control of O&G industrial sites can create a national security dilemma. Policy changes could cause government and private O&G ventures to suffer because of the jurisdiction of capital investors, host states, and "rule of law" arrangements (Walde, 2008). For example, governments could alter policies toward foreign investment or the terms and conditions under which O&G projects were initially conducted.

Table 4
Modeling of safety factor and its node contributors.

Variable Name	Modeling Technique	Modeling Description
Injury	TNORM	Based on statistics, every year OGSC-related fatal injuries in the U.S. vary from 10 to 40 with an average of 24. The variance is approximated as 2.5. (BLS, 2010)
Occupational hazard rate and fatalities	TNORM	The occupational hazard and fatality rate is significantly higher than the death/injury rate and varies from 14 to 199 with an average of 47 every year. The mean is approximated at 0.95 (95%) and variance calculated at 8.
Safety factor	Comparative Expression	The safety factor depends on two factors. If the value of the injury delivery rate is greater than or equal to 20/year and the occupational hazard rate and fatalities exceeds 45, then there is a safety concern related to the OGSC (*True* state), otherwise not (*False* state).

Political and financial agreements may present scenarios that result in decisions that cause severe problems for OGSC activities.

- *Trade agreement problems*: Over the last several decades, changes in political power, government rules and regulations, and legislation policies, have resulted in disruptions in the business world (Jiang et al., 2019). These disruptions have significantly hampered the production and supply of oil and gas during these periods.

The modeling process of *legal factors* is defined below:

As demonstrated in Fig. 3, the legal factor is conditioned upon two nodes: *national security anxiety* and *trade agreement problems. National security anxiety* is designed using Boolean logic and *trade agreement* problems are expressed using the *Ranked Node* approach. If *national security anxiety* is higher than 50% and *trade agreement problems are* greater than the average (medium), then the combined effect resulting from these issues could create legal issues for the OGSC.

Finally, in order to compute the posterior probability of OGSC disruption using the proposed model, a labelled node named “Weight (weighted average)” is created to calculate the weighted value for each variable contributing to OGSC disruption. This weighted value is similar to the weighted mean; however, it is associated with multiples of a particular event and the probability of each happening. The weighted value is computed by summing the products of the weighted variables in the model. Alternatively, the weighted average is derived from the mean probabilities of all the parent nodes in the OGSC as presented in equation (9):

$$WMEAN = \sum W_i S_i = 1, 2 \ldots\ldots n, \ \forall i = 1; 0 < W_i < 1; \sum_i W_i = 1 \tag{9}$$

where i represents the number of variables ($i = 7$ for the proposed model) directly connected to the weighted average node of the OGSC disruption (see Fig. 3) and W_i denotes the weight of the ith variable.

Based on this formula, the *posterior probability of OGSC disruption* being *true* is estimated at 59.04% which means that there is a 59.04% likelihood (chance) that the OGSC might undergo disruption (see Fig. 3).

The description of causal relations among the trigger nodes, main causal nodes, and intermediate nodes that are potentially liable to OGSC disaster are summarized in Table 6. In other words, the simplified

Table 5
Simplified tabular format of Fig. 3 (base BN model).

Node	Child Node	Parent Node
Technical	O&G SC Disaster	Mechanical failure, Scheduling problem, O&G extraction techniques
Mechanical Failure	Technical	–
Scheduling problem	Technical	Delivery delay, Lead time
O&G extraction techniques	Technical	Extraction time, Extraction cost
Delivery Delay	Scheduling problem	–
Lead Time	Scheduling problem	–
Extraction time	O&G extraction techniques	–
Extraction cost	O&G extraction techniques	–
Economic	O&G SC Disaster	Socio economic disruption, Volatility is stock market
Socio economic disruption	Economic	Oil price fluctuation, Recession, Fluctuation in demand
Volatility is stock market	Economic	–
Oil price fluctuation	Socio economic disruption	–
Recession	Socio economic disruption	–
Fluctuation in demand	Socio economic disruption	–
Social	O&G SC Disaster	Psychosocial effect, Cultural and society infrastructure, Remoteness & population
Psychosocial effect	Social	Absenteeism, Worker anxiety, Tend to slow down
Cultural and society infrastructure	Social	–
Remoteness and population	Social	–
Absenteeism	Psychosocial effect	–
Worker anxiety	Psychosocial effect	–
Tend to slow down	Psychosocial effect	–
Political	O&G SC Disaster	Political dispute and unrest, Partnership condition with government
Political dispute and unrest	Political	–
Partnership condition with government	Political	–
Safety	O&G SC Disaster	Injury, Occupational Hazard and fatalities
Injury	Safety	–
Occupational Hazard and fatalities	Safety	–
Environmental	O&G SC Disaster	Accidental waste, Natural disaster
Accidental waste	Environmental	–
Natural disaster	Environmental	Earthquake, Tornado
Earthquake	Natural disaster	–
Tornado	Natural disaster	–
Legal	O&G SC Disaster	National security agency, Trade agreement problems
National security agency	Legal	–
Trade agreement problems	Legal	–
Weight	O&G SC Disaster	–

Table 6
Comparative illustration of predictive inference reasoning.

Scenario	O&G extraction technique	Socio-economic disruption	Worker anxiety	Political dispute and unrest	Occupational hazard and fatalities	Earthquake	Trade agreement problems	Likelihood of OGSC Disaster
Base Case	78.18% (True)	22.65% (True)	60% (True)	67.27% (True)	14 < 47<199	65% (True)	30% Low, 60% Medium, 10% High	59.04%
Scenario 1	100% True	100% True	100% True	100% True	200	100% True	100% High	72.88%
Scenario 2	100% False	100% False	100% False	100% False	25	100% False	100% Low	34.80%

version of Fig. 3 (base BN model) is presented in Table 5.

6. Analysis and results

In this section, we will discuss different types of technical analyses, such as belief propagation and sensitivity analysis, to validate the underlying model.

6.1. Propagation analysis

Belief propagation analysis, also known as *predictive inference (PI) reasoning*, occurs when different observations are set for different nodes to evaluate the impact on the target node. There are two types of propagation that can be conducted on the underlying BN model: *forward and backward*. Forward propagation allows observations about causes to be made to determine the effect, whereas backward propagation permits observations of effects to be inserted and propagated backward to arrive at conclusions about the causes (Fenton and Neil, 2013). During propagation analysis, the probability distribution for an event is predicted based on the contributing factors $M_i = 1\ to\ n$. Each factor used as an input is functioned into the BN model, creating the probability distribution of N in the following way:

$$P(N=Q_k)\sum_{1}^{m^r} P(N=S_k|M_1=m_l, M_2=m_l, \ldots, M_r=m_l) \times P(M_1=m_l, M_2=m_l, \ldots, M_r=m_l)\lim_{x\to\infty} \quad (10)$$

where, r is considered as root nodes, and m_l would be the l_{th} state of n where $l = 1\ to\ m$. Q_k is the k^{th} state of the leaf node, where $k = 1$ to t. $P(N=Q_k|M_1=m_l, M_2=m_l, \ldots, M_n=m_l)$ is the conditional probability distribution when $N = Q_k$.

$$P(M_i|e)\ \forall\ M_i \in M_l \quad (11)$$

In our study, we considered *forward propagation analysis* to predict disaster in the OGSC under a combination of influential factors modeled using historical data and expert opinion. Based on Fig. 4, an illustration of forward propagation is *Oil price fluctuation → Socio-Economic Disruption → Economic Disruption → OGSC Disaster.* The underlying concept of belief propagation is transmission of a message using a message-passing algorithm that passes a parent node A to a child node B. Sometimes, the direction can be reversed depending upon the type of message sent, e.g., a casual support message when child node C is drawn to parent node B. When the message is dispersed from A to B, the conditional probability can be obtained from A to B to its final probability distribution.

To illustrate the application of the forward propagation algorithm, we have considered two distinct scenarios (a) pessimistic and (b) optimistic.

Scenario 1: During the *pessimistic scenario* illustrated in Fig. 4, we have generated and simulated a new scenario by setting the seven different variables to "*true*": (i) the existing *O&G extraction technique* is completely impracticable (100% True state), which means that extraction time and extraction cost are no longer feasible to conduct the extraction operation, (ii) *socio-economic disruption* might reach 100% (True state) due to oil price fluctuation and recession. This means that when a recession hits the USA badly, the international price for oil and O&G consumption demand fluctuate rapidly with serious consequences that lead to socio-economic disruptions, (iii) *worker anxiety* reaches its peak (100% true) due to dissatisfaction that stems from working conditions and mental and physical stress, (iv) *political dispute and unrest* are highly likely (100% true) to trigger political tension that will ultimately impact the performance of the OGSC, (v) due to poor safety policies, *occupational and hazard fatalities* will occur more than the maximum (~200/yr.), (vi) earthquakes might frequently impact and disrupt regular operations of the OGSC, and (vii) trade agreement problems might become a major concern (100% true) due to a change in political powers, government regulations, and legislation policies. These seven factors belong to seven different groups and were chosen in such a way that these are most likely to happen in real-world situations. It is apparent from Fig. 4 that these observations together disseminate an adverse impact on the overall probability of OGSC resilience and subsequently enhance the probability of an OGSC disaster from 59.04% to 72.88%.

Scenario 2: On the other hand, an *optimistic scenario* accounts for a false state in five out of seven of the aforementioned variables along with a low *occupational hazard/fatality rate (=25),* which means that few injuries or accidents occur in the OGSC, and few *trade agreement problems* (=*low* state), which signifies that there is a low likelihood that trade agreement problems will give rise to legal disputes and ramifications in the O&G sector. A false state actually presents the absence of a pessimistic situation. Described succinctly, the optimistic scenario will demonstrate the exact opposite situation of the pessimistic scenario, ultimately enhancing the performance of the OGSC network. The combined effect of these variables positively impacts the OGSC performance and brings down the likelihood of OGSC disaster significantly from 59.04% to 34.80% (see Fig. 5). A comparative analysis between the new scenario and base case is summarized in Table 6 and illustrated in Figs. 4 and 5.

6.2. Sensitivity analysis

Sensitivity analysis (SA) is a validation tool that assesses the influence of causal factors on the outcome of a target node under a given set of assumptions. More precisely, sensitivity analysis demonstrates how various sources of uncertainty in an analytical model would contribute to the overall uncertainty of the underlying model. One of the benefits of SA is visualization, which allows relevant variables to be depicted using elaborative graphs. SA gives a comprehensive understanding of possible future outcomes depending on the available data. In this study, the aim was to identify the relative importance of each node that directly influences the likelihood of an OGSC disaster.

For a BN, sensitivity $I(\rho)$ of the defined parameter $\rho = P(W_i|\sigma)$can be represented as follows:

$$I(\rho) = \frac{1}{pq}\sum_{m,n}\frac{\delta P(M|N)(\rho)}{\delta\rho} \quad (12)$$

where, p and q are the number of values for M and N respectively. In the

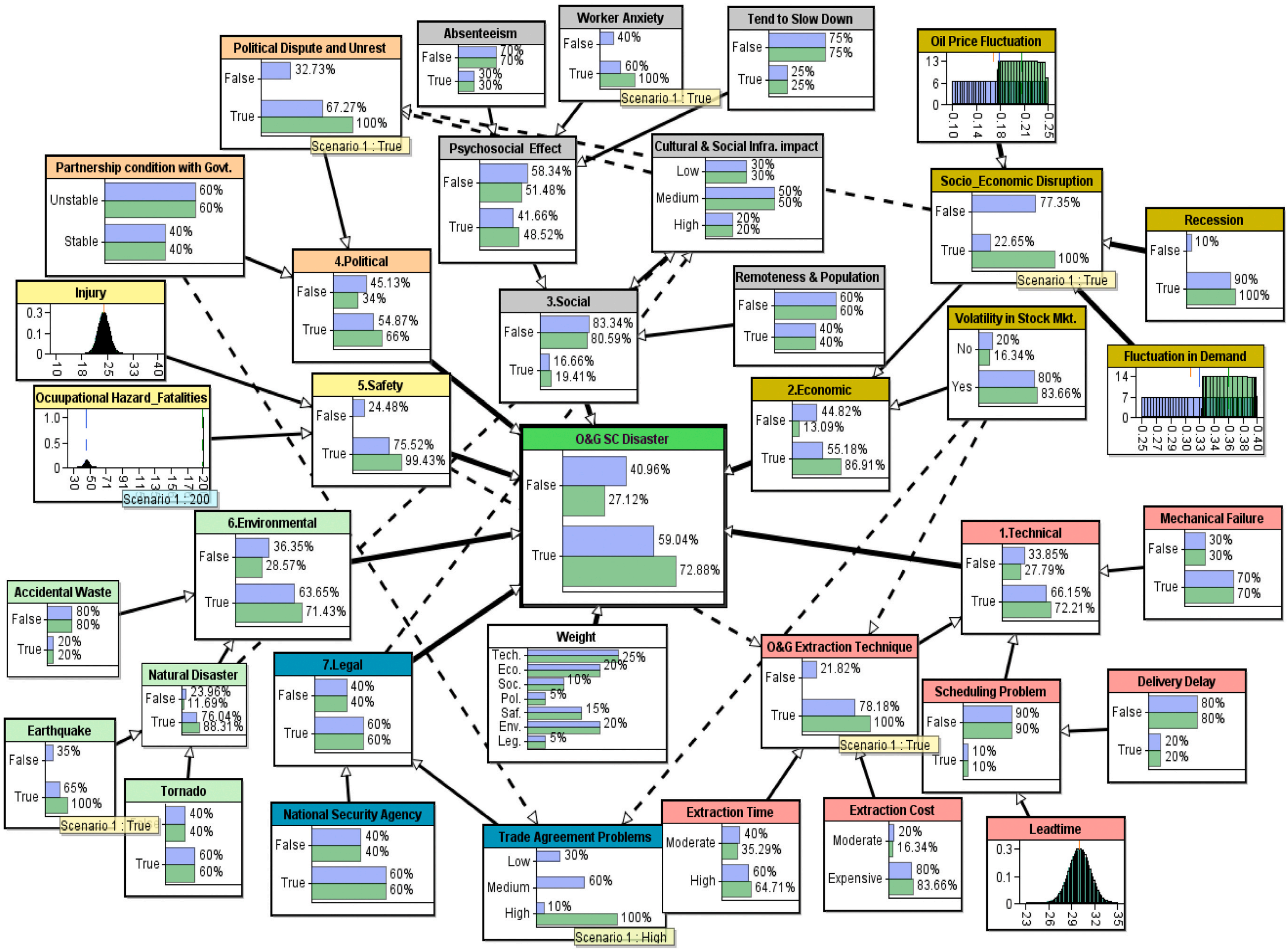

Fig. 4. The developed BN model for measuring disruption of the OGSC network. (Scenario 1).

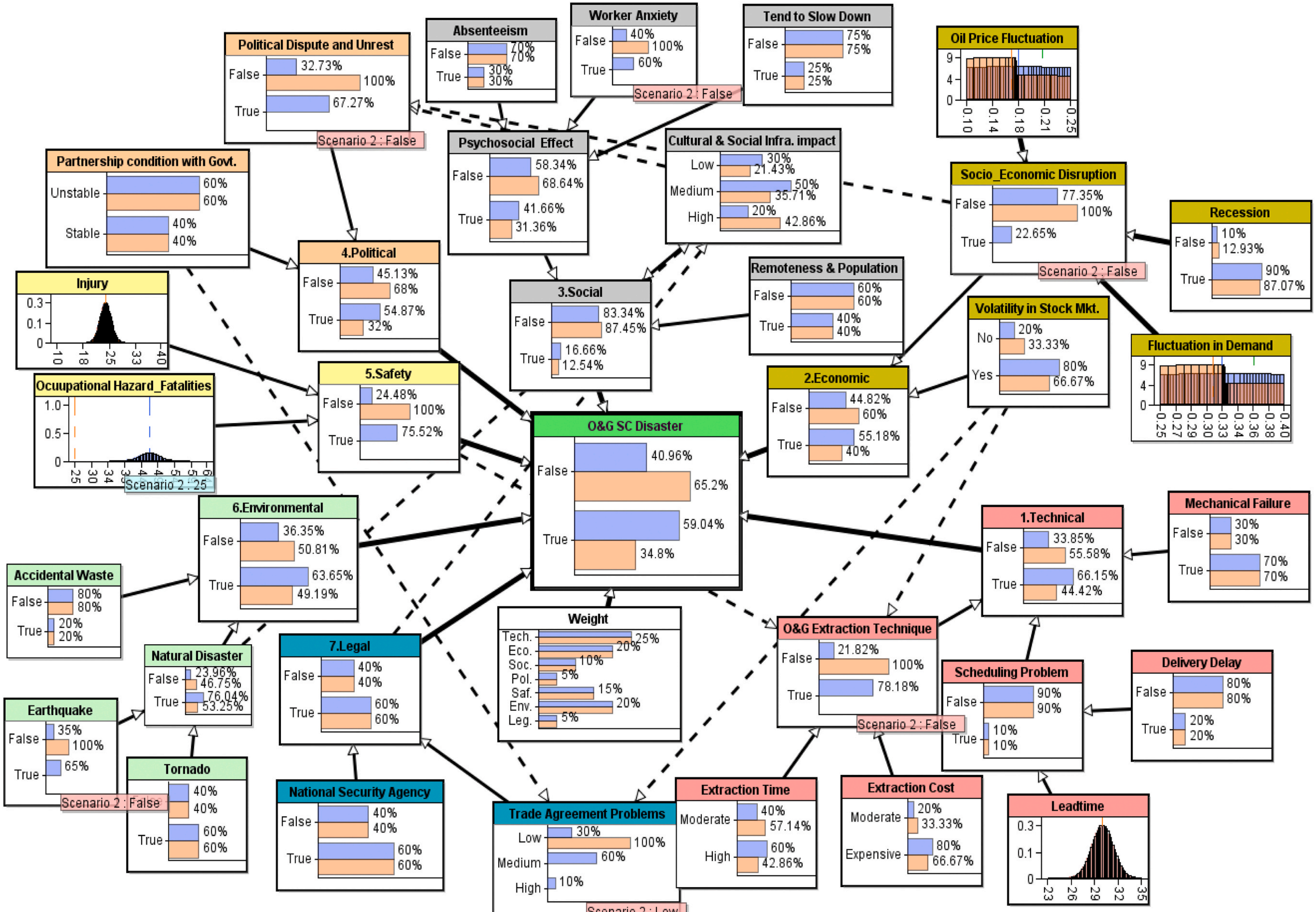

Fig. 5. The developed BN model for measuring disruption of the OGSC network. (Scenario 2).

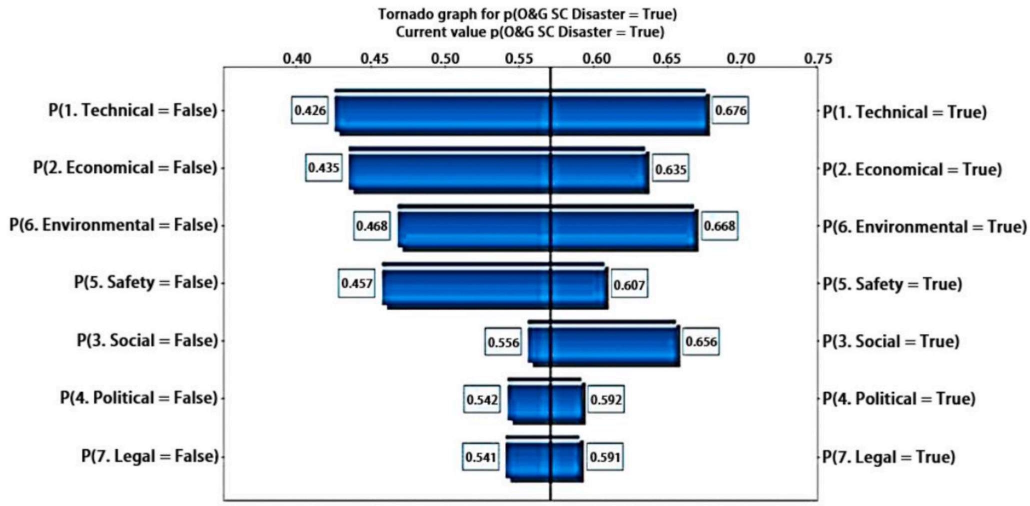

Fig. 6. Sensitivity analysis of the OGSC disruption (Tornado Graph).

above factors, S_1 and S_2 are two random nodes. The parameter for node B is $\rho = P(W_i|\sigma)$, and sensitivity of S_2 relative to S_1 can be represented using the following equation:

$$IT(S_2) = \frac{1}{pq}\sum_{j=1}^{p}\sum_{i=1}^{q} I(\rho_{ij}) \tag{13}$$

where, p and q are the number of values for S_1 and S_2.

To depict the relative importance of different causal factors such as *technical, economic, social, political, safety, environmental,* and *legal* on OGSC disruption, *OGSC disruption* is set as the target node, and the impact of its causal factors are evaluated by conditional probability. The sensitivity analysis of *OGSC disruption* is demonstrated in Fig. 6 in the form of a "tornado graph". The width of the bars of the tornado graph represents a measure of the impact of the corresponding factor on *OGSC disruption.* The bars are organized in descending order based on width, which allows practitioners to easily understand the relative importance of each factor. Fig. 6 demonstrates the influence of a set of contributing factors (i.e., *technical, economic, social, political, safety, environmental,* and *legal*) on *OGSC disruption* when these variables are "*True*". Fig. 6 shows that the *technical* factor changes from 0.426 (when OGSC is false) to 0.676 (when OGSC is true), while the impact of legal and political factors are limited to a narrow range compared to other factors. The formal presentation of this figure indicates that the *technical* factor has the highest impact, while *legal* and *political* factors have the lowest influence on disruption of the OGSC.

To justify the results of the tornado graph, we compared empirical results to our real-world scenario. The inherent criteria for an OGSC disruption are not always equally likely. However, after categorizing the factors, we were able to determine the likelihood of events that cause OGSC disruption. Based on the output, it is apparent that *technical* and *economic* factors are the variables most likely to cause oil and gas supply chain disruption, which is plausible when compared to real-world situations.

Considering the technical aspects of the oil and gas extraction process, it is appropriate to mention that O&G management needs to be careful when operating and maintaining machines, piping, and drilling equipment during extraction, especially at the Gulf of Mexico Eagle Ford, Utica, Alaska, and other prominent areas. The O&G industry is capital-intensive and its success is heavily dependent on the efficient functioning of proprietary technology. Any downtime caused by equipment failure will have serious negative consequences on the costs and revenue streams of O&G companies due to the shear volumes involved. Furthermore, oil and gas industries need to deploy efficient workers to avoid technical risks such as extraction delay, lengthy process times, and most importantly consumer cost. Also, oil and gas transportation risks need to be handled by mitigating scheduling problems such as failure time to serving, hydraulic fracturing, and timely responsiveness. The probabilistic measures from our model justify the scheduling problem as well as other relevant technical problems of overall OGSC disruption.

The second important factor for OGSC disruption, "*economic factor*", reflects our real-world scenario. After a few shocking years of market abnormality, gas prices have continued to increase due to operational and financial risk management strategies in the U.S. market. Fluctuating international oil prices may have some drawbacks in the U.S. due to the impact on costs and prices of goods and services in different essential sectors. Many industries are hugely dependent on the O&G sector and any volatility diminishes efforts to run their operations in a profitable manner. Highly unstable oil prices make it difficult, not only to manage day to day operations efficiently, but to encourage capital investments in sectors that are dependent on the O&G sector. However, if controlled, economic consequences such as the recession during the 2008–2010 fiscal years could potentially be avoided. Hence, the outcome from our model indicates that price and demand of oil and gas need to be standardized and controlled to prevent unwanted volatility in the market.

The Tornado graph illustrated in Fig. 6 implies a reasonable understanding that legal and political factors are less likely to cause OGSC disruptions than technical and economic factors. This can be observed from the Tornado graph which indicates a value range of 0.542–0.592 for political factors and 0.541 to 0.591 for legal factors, while technical and economic factors have ranges of 0.426–0.676 and 0.435 to 0.635 respectively. Since government rules and regulations are sufficiently flexible to adjust the terms for oil producers, legal and political factors can be curtailed or at least minimized to prevent disruption in O&G supply chain operations. For example, negotiation and dispute resolution provide mechanisms to control the occurrence of energy crises and develop local and international supplier relations. On the other hand, less predictable risks such as technical failures, economic volatility, or rare environmental disasters, with low probability of occurrence but severe impact are more likely to result in major financial losses despite the O&G industry's best efforts at formulating contingency or crisis management plans. The results support real world observations since governments will not allow legal and political factors to disrupt the OGSC for prolonged periods of time due to the significance of the O&G industry to economic activity and growth.

6.3. Practical implications

This study presents a comprehensive modeling framework to assess and predict the OGSC disruption by highlighting the main contributory factors that can lead to these disruptions. The oil and gas industry is intricately tied to national economic and social prosperity and any disruption in the OGSC could lead to astronomical impacts in these spheres. The BN model provides a basis for identifying and prioritizing risk events to support the development of risk mitigation strategies. The results show that technical, economic, and environmental factors have the greatest likelihood of causing OGSC disruptions. Therefore, supply chain practitioners in the O&G sector can utilize this knowledge to prioritize the development of risk mitigation strategies, particularly at the sub-factor level, to address potential disruptions associated with mechanical failure, extraction, scheduling, socio-economic impacts, stock price volatility, natural disasters and accidental waste. The model also provides a starting point for evaluating the impact of disruptions in the OGSC on other supply chains and industry sectors.

The proposed model and the overall outcome of this research provide a number of managerial insights that will be handy for industrial policymakers, oil and gas firms, other sectors that depend on the oil and gas industry, and researchers in academia. Firstly, the proposed disruption assessment model can be used to assess the probabilistic disaster for any specific oil and gas industry, which in turn will be valuable for disaster preparedness of both O&G firms and other sectors that depend on O&G. Additionally, this model can be applied to any specific tier of the OGSC to assess the vulnerability of that specific facility. The outcome of this model emphasizes the dominance of the technical factors over the other factors contributing to disruption. Therefore, more resources should be allocated to strengthening the technical infrastructure of the OGSC and devising and implementing preventive measures to minimize risk impacts. For example, O&G extraction companies can establish continuous monitoring systems and administer periodic preventive maintenance for their machines and equipment to avoid any extraction, scheduling, and delivery delays due to technical failures. In addition, O&G extraction companies may undertake different measures such as, close monitoring of stocks, accurate demand forecasting, and price adjustments needed to ensure their economic soundness. Further, environmental policies can be reviewed and enforced with adopting more waste recycling measures. These measures will work directly towards environmental soundness. Similar to other factors, legal and political factors should still be of interest with minimum emphasis among the seven factors responsible for OGSC disaster. In summary, this research opens up the avenue for advanced strategic planning that will help develop more resilient and robust infrastructure in the OGSC and dependent firms.

7. Conclusion

This research paper proposes a comprehensive Bayesian network (BN) model to predict the vulnerability and disruption of the OGSC network, especially for the United States. After conducting a preliminary theoretical study of the existing literature, seven factors and several subfactors responsible for OGSC disruption were identified. We then quantified the relevant factors and subfactors and fed them into the BN network. Finally, simulation was conducted to predict the overall vulnerability of the OGSC network. The original elements of our research are summarized below:

- The model is developed based on real-world cases of oil and gas supply chain disruption.
- The prime factors that affect supply chain network disruptions are outlined and quantified.
- A real case study of OGSC was adopted to predict the disruption using a developed BN framework.
- A different set of analyses was adopted to draw further insights and validate the output of the proposed model.

In this study, academic and industrial viewpoints were also critically considered. For academia, the proposed BN network could serve as a benchmark for future reference on disruptive sub-factors affecting the OGSC.

The OGSC is the lifeblood of many organizations and virtually every economy. From an industrial viewpoint, policy makers, executives and senior management can utilize this study to explore O&G industries and solve in-depth problems in at least four ways. First, this model could be incorporated into a more systemic analysis to explore and predict possible ripple effects of disruptions in multiple industries and their supply chains. For example, a disruption in the OGSC could lead to supply and demand imbalances, driving up the price of oil. A resulting spike in fuel prices could impact costs in several industries such as aviation, heavy manufacturing, logistics and transportation, with a massive spillover of cost into downstream industries such as processing, assembly, and retail operations. Ultimately the cost of goods to the end customer will be impacted. By extending the model and including it in a systemic analysis, the impact of disruptive shocks on all related enterprises and the consumers could be better assessed. Second, a BN model could be very useful as a post-auditing tool to evaluate progress in mitigating internal OGSC risks to determine where control procedures, including training is necessary. Another potential use would be to conduct scenario analyses within the OGSC for the purpose of developing mitigation solutions and crisis management plans in advance to avert long-term problems. Fourth, in addition to direct and indirect operational consequences of OGSC disruptions, a BN model could be incorporated into network development and strategic development plans to assess opportunities that stem from weak links in the OGSC. Such plans might include alternative investments and redundancies to offer a more robust and resilient energy supply chain.

Robust supply chain management activities can be executed by using both theoretical and analytical approaches. This study could also be further augmented in different ways. A time-dependent dynamic Bayesian Network model could be initialized to monitor the OGSC performance and the consistency of the model over time. Also, information theory that considers the state of uncertainty and mutual interdependencies between the different factors impacting the probability of OGSC disaster could be applied. Further, the Delphi technique could be adopted to better elicit the node probability table (NPT) for the BN variables.

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