A scenario analysis under epistemic uncertainty in Natech accidents: imprecise probability reasoning in Bayesian Network

Qiuhan Wang¹, Mei Cai¹,² and Guo Wei³

¹ School of Management Science and Engineering, Nanjing University of Information Science & Technology, No. 219, Ningliu Road, Nanjing, Jiangsu, People’s Republic of China
² Research Center of Risk Management and Emergency Decision Making, Nanjing University of Information Science and Technology, Nanjing 210044, People’s Republic of China
³ Department of Mathematics and Computer Science, University of North Carolina at Pembroke, NC, United States of America

E-mail: caimei@nuist.edu.cn

Keywords: risk assessment, natech accidents, bayesian network (BN), evidence theory

Abstract

The increasing frequency and severity of Natech accidents warn us to investigate the occurrence mechanism of these events. Cascading disasters chain magnifies the impact of natural hazards due to its propagation through critical infrastructures and socio-economic networks. In order to manipulate imprecise probabilities of cascading events in Natech scenarios, this work proposes an improved Bayesian network (BN) combining with evidence theory to better deal with epistemic uncertainty in Natech accidents than traditional BNs. Effective inference algorithms have been developed to propagate system faulty in a socio-economic system. The conditional probability table (CPT) of BN in the traditional probability approach is modified by utilizing an OR/AND gate to obtain the belief mass propagation in the framework of evidence theory. Our improved Bayesian network methodology makes it possible to assess the impact and damage of Natech accidents under the environment of complex interdependence among accidents with insufficient data. Finally, a case study of Guangdong province, an area prone to natural disasters, is given. The modified Bayesian network is carried out to analyze this area’s Natech scenario. After diagnostic analysis and sensitivity analysis of human factors and the natural factor, we are able to locate the key nodes in the cascading disaster chain. Findings can provide useful theoretical support for urban managers of industrial cities to enhance disaster prevention and mitigation ability.

1. Introduction

Technological systems, such as chemical facilities, oil and gas pipelines, or nuclear facilities are vulnerable to natural hazard impacts. These impacts can trigger fires, explosions and releases of toxic or radioactive substances with potentially magnified social, environmental and economic consequences. Technological accidents triggered by natural hazards are known as Natechs. Natech events were studied for the first time at the end of the 1970s [1]. In recent years Natech risk research has gained importance [2–6]. Natechs are high-consequence and low probability events, breaking away from traditional risk assessment [7]. The fragile environment is merging with the serious social and economic vulnerability, resulting in the potential cascading crisis. The increasing frequency and severity of Natech accidents force us to delve into the occurrence mechanism of these events.

Natech accidents feature complex consequences through synergistic effects between the natural and technological hazards [8]. The March 11, 2011 Tohoku earthquake killed 18,508 people (National Police Agency. Report of the Damage Caused by the 2011 Tohoku Earthquake and Tsunami in Japan) and seriously damaged the Fukushima Daiichi nuclear power station (NPS), causing meltdown of the reactor and the release of radioactive materials [9]. The serious consequence of the 2011 Tohoku earthquake forced the whole world to consider more realistically the problem of Natechs. In order to explain a series of interacted failures in socio-economic systems, the word ‘cascading’ is often associated with the metaphor of toppling dominoes [10].
Natechs may have a bearing on the cause-and-effect relationship that is a feature of most ‘cascading disasters’. Natural disaster risk is transmitted to natural or social domains [11]. The domino effect has a particular relevance in Natech events. Actually, domino effect leads to complex scenarios. Due to the high degree of dependency on networks of modern society, failures can propagate through critical infrastructures [12]. The propagation of domino effect is a very complex process involving many random variables and probabilities [13].

Population growth, migration to urban areas, and proximity to industrial developments in hazard-prone areas have aggravated communities’ exposure and vulnerability [6]. Damage to critical infrastructures needs to be analyzed as a cascading effect of major natural hazards. The consequences of disasters are the result of the combined effects of disaster exposure, local social vulnerability and disaster response capabilities. Modern population’s high dependence on critical infrastructures and networks enables the risk of disasters to spread through socio-economic systems. Losses and casualties depend not only on the hazard intensities but also on urban exposure and vulnerability. When vulnerabilities of a socio-economic system overlap and interact, the secondary system failure triggered by the original one may generate greater impact than the original one. Scenarios can be used to identify critical dependencies of cascading disasters.

Natech events cover the domains of natural and human systems. Cascading impacts cause great disasters by disrupting critical infrastructures because of closely linked human systems. For example, floods in undated industrial premises and caused toxic smoke emissions; an earthquake caused major nuclear accidents and caused fires and explosions in refineries, petrochemical and other industrial facilities. Disaster risk-reduction frameworks have not really addressed the issue of technological risks in general, although they usually highlight Natech as an example of a cascading multi-hazard risk. Decision support systems and impact assessments methods are proposed to understand of cascading disasters in interdependent systems [14]. These academic works have been elaborated to understand better interdependencies and complexity. However, the Natech scenario remains vague and lacks precise description models [15]. The scenario description is a challenging factor in Natech.

Bayesian network (BN) as a robust technique has been widely used in the field of risk assessment [16]. A Bayesian network as a graph in which nodes represent events, for example, rainstorm, hurricane and casualties and economic losses, is often employed for complex causal and uncertain problems [16, 17]. Causal interpretation of the structure can be useful tool of explanation of cascades in Natech accidents. Causal mechanisms supply a general prototype for decision makers participating in the risk management. These successful applications [16, 18–20] also fully demonstrate that Bayesian network technology is a powerful uncertainty reasoning method.

Besides, uncertainty is another challenge in Natechs. In Bayesian modeling, we need quantify two main types of uncertainty. One is Aleatoric uncertainty which captures noise inherent in the observations (measurement noise) and cannot be reduced even if more data were to be collected. The other is epistemic uncertainty which captures our ignorance and can be explained away given enough data [21]. Some approaches [21–23] with the explicit goal of minimizing aleatoric noise were proposed. In contrast, to better manage epistemic uncertainties, we need to collect enough data based on the historical events. While Natech events are low frequency events, conventional approaches to understanding probability distribution of such events are often incapable. Decision-making performance’s quality decreases when the complexity of the problem increases and the time pressure becomes larger. Yet accurate estimation of risk is necessary for such high-consequence events. Imprecise probabilities, because of their advantages of describing event’s uncertainty have effectively been used when solving data scarcity and data incompleteness problem [19]. Dempster-Shafer Theory (DST)—also known as evidence theory [24]—has been employed as a promising technique for manipulating imprecise probabilities [19, 25, 26]. DST has been widely used recently in the fields of uncertain reasoning, multi-source information fusion, and decision making with uncertain information [27]. Natech risk fuses natural factors and human factors. A paradigm change of managing Natechs is required from traditional risk management to a multi-hazard, multi-sectoral one [3].

The Bayesian network technique and DST have been applied to Natech risk assessment in this paper. We can predict an urban system unreliability and compute diagnostic indices by means of BN. At the same time, sensitivity analysis is taken to find which parameters should be modified to lower the degree of objective parameters to acceptable levels. Sensitivity analysis can improve the prediction of an area’s ability to resist disasters. We can deeply study the cascading disasters chain by changing input variables or by the analysis of interactions between variables [28]. Many scholars study the sensitivity and potential relationship of their variables based on sensitivity analysis quantitatively in macroeconomic management and sustainable development [29–33], environmental science and resource utilization [34–36] and other fields. Under this quantitative analysis, we can provide more decision-making basis for the government to formulate sustainable development policies.

The rest of the paper is structured as follows. A typical Natech scenario is described in section 2. A Natech analysis framework is divided into the network model and risk assessment. Section 3 constructs a BN to describe...
cascading events in Natech scenarios for efficient computational investigation of risk management. Section 4 provides the reasoning technique of BN for Natech scenarios. Rules of belief mass propagation combined with evidence theory are also given. In section 5, a case study of Guangdong province is given. Sensitivities analysis is carried out to find key factors of a Natech accident. Section 6 is the advantages and limitations of our approach.

2. A representative Natech analysis framework

In this section, we simulate the disaster effects and the final possible consequences of natural disasters by constructing a typical Natech structure. In the process of Natech disaster development, the first set of actions of the system during the evolution of a contingency represents the ‘first-stage reaction’, which implements short term responses (water, voltage controller, plant equipment protection system, urban utilities system), and long-term interventions (changing the state or setting of generators, pumped storage station, drainage pipeline, etc). When the natural disaster is ended, the ‘second stage reaction’ will be carried out examining the existing protection and disaster loss data. In the second stage, we will analyze the causes and consequences of the natural disaster and modify urban infrastructure or improve the remedial measures pertinently to improve the city resilience.

The evolution of Natech system is initiated by a trigger event, which can be selected from a series of contingencies. Triggering events represent the materialization of one or more threats. For example, typhoon, as an instance of natural threat, may cause rainstorm and waterlogging, which damages urban construction and industrial equipment, disconnects some lines, leading to the collapse of urban utilities system.

We present a figure to describe a typical Natech analysis framework (see figure 1). The figure is divided into 2 parts. The first part describes the network model of triggering events covering network status, operational decision and evaluation of impact. The second part is the risk assessment of the disaster.

Network modeling and optimal operational decision layer provide the physical impact of natural disasters on existing networks, and it is a basis for designing countermeasures. In addition to studying the total network data, the inputs also include a threats catalog and a countermeasure catalog. The threat catalog is a group of possible threats to the network under study, such as rainstorm caused by typhoon. The countermeasure catalog includes new interesting remedial measures, protection schemes and enhancement measures. The possible threat will bring the system to $S_0$ status after the first-stage reaction. Related departments will take short term responses $OD_1$ to reduce disaster risk immediately to avoid excessive economic losses and casualties. And $OD_2$ are long term interventions. The impact of triggering events on the social system in this state $I_1$ will be evaluated through the current loss $L_1$ (including economic losses $L_{1e}$, environmental pollution $L_{1i}$ and casualties $L_{1k}$), and the urban resilience $R_1$ will be inferred. When the disaster is over, the system will enter the second-stage $S_2$. After
the implementation of certain prevention and rescue measures, the urban resilience $R_2$ will be inferred. The possible impact on the next disaster $I_2$ will be evaluated by predicting the relevant loss $L_2$.

3. Research methods

In this section, we provide the analytics that can cross key barriers to building integrated Natech scenarios from the convergence of natural and technique hazards. First, we present hazard chain, with a specific focus on the analysis of causal relationship among multi-hazards. Then we construct a BN to describe cascading events in Natech scenarios for efficient computational investigation of risk management.

3.1. Cascading disasters chain

Cascading disasters begin with a single primary threat and then occur as sequences of events [37]. During Natech events, the risk of cascading disasters is generally higher than during conventional technological accidents [3].

The interaction between different disasters is intrinsically difficult to model due to the lack of data and the unavailability of concurrent hazard models (‘hazard interaction problem’) [38].

The events in a cascading disaster chain commonly have causal relationships. How to model causal mechanisms in a Natech scenario is theoretically important and practically critical. The way of representing cascading events is a diagram of nodes and arrows. Nodes are divided into two categories: parent events and child events. The relationships among nodes are divided into three categories: series relationship, parallel relationship and the mixed relationship.

3.1.1. Series relationship

Serial events refer to a disaster chain where the initial event $X_1$ triggers a secondary event $X_2$ and $X_2$ triggers a tertiary event $X_3$, and so on. These events have a series relationship. There is an influence of event $X_1$ on event $X_2$, and another influence of event $X_2$ on event $X_3$. The structure corresponding to this situation is shown in figure 2.

3.1.2. Parallel relationship

Parallel relationships are divided into two classifications: head-to-head and tail-to-tail.

Head-to-head parallel events refer to a disaster chain where the initial event $X_1$ triggers several secondary events $X_2, X_3, \ldots, X_n$ at the same time. There is an influence of event $X_i, i \in [2, n]$ on each event $X_i, i \in [2, n]$, and events $X_2, X_3, \ldots, X_n$ are conditionally independent given. The simplest structure with two child events $X_2, X_3$ corresponding to this situation is shown in figure 3.

Tail-to-tail parallel events refer to the disaster chain where several initial events $X_1, X_3, \ldots, X_n$ happening at the same time can trigger the secondary event $X_2$. The simplest structure with two parent events $X_2, X_3$ corresponding to this situation is shown in figure 3. There is an influence of event $X_2$ on event $X_1$, and another influence of event $X_3$ on event $X_1$. Event $X_2$ and $X_3$ happen quite differently, without any form of interactions. The simplest structure with two parent events $X_2, X_3$ corresponding to this situation is shown in figure 4.
3.1.3. Mixed relationship
The mixed events refer to a chain that includes both head-to-head and tail-to-tail parallel events. Mixed events refer to the disaster chain where event $X_1$ triggers the secondary events $X'_1, X'_2, \ldots, X'_n$ at the same time. Event $X_1$ is decided by events $X_3, X_5, \ldots, X_m$. The simplest structure corresponding to this situation is shown in figure 5.

3.2. The graphical structure of a cascading disasters chain
The assessment of a Natech accident can be reflected from three aspects, environmental pollution, casualties, economic loss. After analyzing a typical Natech structure, we determine the basic events, intermediate events and result events. The evolution relation of this cascading chain is often described by a graphical structure. The description of events in a Natech Scenario is shown in table 1.

Interactions between causes and effects can be modeled using Bayesian networks, which combine network analysis with Bayesian statistics [39]. We adopt a BN in which a directed acyclic graph (DAG) is used to represent the evolution process of cascading disasters in a Natech. In a DAG, $G = (N, A, D)$, $N$ is a directed graph, $N$ is a set of nodes which represent disaster events; $A$ is a set of arcs and $D$ is a set of probability distributions describing the statuses of nodes as shown in figure 6.

The probability of an event induced by another event is decided by many factors, such as urban environment. Some disasters are not easy to happen in specific environments because of relatively perfect urban infrastructures while other disasters are very easy to happen because of imperfect urban infrastructures. The inputs of this BN model are from nature factors and human factors. Natural hazard $X_i$ has no incoming edges and its probability is not decided by the state of other nodes. $X_i$ is a node describing a random variable. Different types of hazards have different probability distributions. The marginal probabilities of Local aid resources shortage ($X_5$) and Emergency aid resources shortage ($X_6$) are obtained from historical data. Urban utilities network system is designed as a parallel system of multiple lines to improve the security of the system. Every line may react different to a natural hazard. So urban utilities network system failure ($X_4$) of line $i (i = 1, 2, \ldots, n)$ has the parent node $X_i$. Urban utilities network system failure ($X_4$) is the combination of multiple lines. Local aid resources shortage ($X_5$) and Emergency aid resources shortage ($X_6$) and urban utilities network system failure ($X_4$) are related to the level of regional economic development. We can induce the Resilience ($X_{16}$) from these three factors.

For any child node $X_j$, we would have the conditional probabilities $P(X_j | X_{i1}, X_{i2}, \ldots, X_{in})$ that define how the state of $X_j$ is decided by the states of $X_{i1}, X_{i2}, \ldots, X_{in}$. It is a conditional probability distribution that quantifies the
| Feature       | Node name                  | Description                                                                                                                                                                                                                                                                                                                                 | State                |
|---------------|----------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------|
| Natural factor| Natural hazard ($X_1$)     | Natural hazard refers to the natural phenomena that bring harm to human survival or damage human living environment, including drought, high temperature, flood, typhoon, rainstorm and so on.                                                                                                                | True (happening)     |
| Human factors | Waterlogging ($X_2$)       | Waterlogging refers to the phenomenon of waterlogging disaster in the city due to heavy precipitation or continuous precipitation exceeding the urban drainage capacity. Serious waterlogging will lead to the collapse of urban drainage system and affect daily life. The total number of typhoons was obtained from the China Weather Typhoon Network, and the number of times of waterlogging caused by typhoons was collected from the news reports. The prior probability of waterlogging under typhoon conditions is obtained. | False (not happening) True (happening) |
|               | Damage_building ($X_3$)    | The damage degree of buildings determines the damage degree of equipment related to these buildings, especially storage tanks and pipelines.                                                                                                                                                                                                   | False (not happening) True (happening) |
|               | Urban utilities network failure ($X_4$) | Urban utilities network refers to urban infrastructure for public utilities ranging from electricity, telecommunications to water. There are usually multiple networks in parallel to ensure the city’s function proper. To improve the security of urban utilities network, there are usually several parallel networks $X_i$ ($i = 1, 2, \ldots, n$) running at the same time. The failure of urban utilities network means disorder of urban infrastructure for public utilities ranging from electricity, telecommunications to water. | False (not happening) True (out-of-order) |
|               | Local aid resources shortage ($X_5$) | Local aid resources refer to the general term of production factors providing medical services, usually including personnel, medical expenses, medical institutions, medical beds, medical facilities and equipment, knowledge, skills and information, etc.                                                                                     | False (order) True (out-of-order) |
|               | Emergency aid resources shortage ($X_6$) | Emergency aid resources refer to the emergency aid materials, emergency aid equipment and emergency rescue team that can be mobilized at the first time, as well as the emergency resources that can be provided by neighbor cities.                                                                                                             | False (order) True (out-of-order) |
|               | Medical resources shortage ($X_7$) | Medical resources refer to the combination of local aid resources and emergency aid resources. Medical resources shortage is the result of a comprehensive influence of Local aid resources shortage and Emergency aid resources shortage                                                                 | False (order) True (out-of-order) |
|               | Damage_equipment ($X_8$)   | The damage of storage tank, pipeline and chemical equipment will lead to the leakage of toxic, flammable and explosive gases or substances                                                                                                                                                                                                   | False (order) True (happening) |
|               | Supply interruption ($X_9$) | Supply interruption such as water cut-off and leakage can easily cause great economic losses and casualties. Interruption of water, electricity and communication supply are influenced by natural hazard and the urban infrastructure construction.                                                                                                                                     | False (Supply system normal) True (Supply system abnormal) |
probabilistic dependency between this node and its parents. When propagating probability in a BN, there are three types of basic connections: serial, diverging and converging. And they correspond to the three given cascading events’ relationship categories: series events, head-to-head parallel events, and tail-to-tail parallel events. Bayesian networks will be used to evaluate or predict Natech accidents.

### 3.3. Reasoning of a BN for Natech scenarios based on evidence theory

The probability to measure the likelihood of a random event is traditionally expressed as a number between 0 and 1. In absence of sufficient data or data of sufficient accuracy, point probabilities or probability distributions to characterize Natech event’s uncertainty would be impossible. We apply evidence theory to manipulate uncertainty of Natech events in a BN. The corresponding propagation rules will be governed by imprecise probabilities.

#### 3.3.1. Basic belief assignment

According to DST, all the possible states (mutually exclusive and collectively exhaustive) of an event are presented as singletons in a set known as the frame of discernment $\Omega$. In a cascading disaster chain, nodes of natural and human factors are binary variables with two states (True or False). All the possible states of a node are

| Feature | Node name | Description | State |
|---------|-----------|-------------|-------|
| Traffic confusion ($X_{10}$) | Traffic confusion is easy to cause production activity blocked and even effect global supply chain. In a nutshell, it will cause a lot of economic losses. | True (Traffic_interrupt) |
| Material_leakage ($X_{11}$) | Harmful substances leakage will lead to poisoning, fire, explosion and other disasters. Serious leakage will cause environmental pollution and a large area of casualties. | False (Traffic_smooth) True (Severe) |
| Epidemic ($X_{12}$) | Epidemic refers to infectious diseases like malaria that can infect a large number of people and can spread widely in a short period of time. If hospitals and social security can’t supply enough sources, it will cause a lot of casualties and improve the vulnerability of the city. | False (Epidemic not spreading) True (Epidemic spreading) |
| Loss evaluating indicators | Environmental pollution ($X_{13}$) | The leakage of toxic substances in environmental pollution will lead to environmental pollution, and then improve the vulnerability of the city. | Serious |
| | Casualties ($X_{14}$) | Casualties are caused by leakage of toxic substances and infectious diseases. If the casualties are serious, they will have a great impact on the vulnerability of the city. | Medium Slight Serious |
| | Economic loss ($X_{15}$) | The economic loss of a city is closely related to the severity of the disaster and the resistance of the city. Therefore, the degree of economic loss can reflect the vulnerability of the city. | Medium Slight Serious |
| City managing Level | Resilience ($X_{16}$) | It refers to the ability of a city to resist disasters, reduce disaster losses, and reasonably allocate resources to recover from disasters. City resilience varies and reflects the level of urban management. | Medium Weak |
presented as $\Omega = \{ H_1, H_2 \}$, where $H_1$ means True and $H_2$ means False. A focal set $A_i$ is defined as $A_i \in 2^\Omega = \{ \Phi, \{ H_1 \}, \{ H_2 \}, \{ H_1, H_2 \} \}$. Where $\Phi$ is an empty set.

The role of the focal element $[H_1, H_2]$ is to characterize our uncertainty on the real state of an event without commitment. It means that the event can be in the state $H_1$ or $H_2$. $m(A_i)$ is belief mass measuring the degree to which a particular state in $\Omega$ belongs to $A_i$ [40]. $m(A_i)$ satisfies these conditions [24]:

$$0 \leq m(A_i) \leq 1$$
$$m(\Phi) = 0$$
$$\sum_{i=1}^{2^\Omega} m(A_i) = 1$$

When we collect information from different reliability databases or experienced experts, we often obtain imprecise probability which is in the form of lower probability ($\underline{P}$) and upper bound probability ($\overline{P}$) as the probabilities of the states of an event. Imprecise probability expresses the uncertainty about the states of the node. Lower probability equals to belief ($\text{Bel}$) and upper bound probability equal to plausibility ($\text{Pls}$) of each focal set $A_i$. Their relationship is $\overline{P}(A_i) = \text{Bel}(A_i) < P(A_i) < \text{Pls}(A_i) = \overline{P}(A_i)$.

We use evidence theory to handle imprecise probabilities and design reasoning rules accordingly. We can obtain following relations [41]:

$$\text{Pls}(A_i) = 1 - \text{Bel}(A_i) \quad (1)$$
$$\text{Bel}(A_i) = 1 - \text{Pls}(A_i)$$

Figure 6. A general BN for urban failure system.

Figure 7. A case in which A and B are connected to C via AND gate.
where $A_i'$ is the complement of $A_i$, function (1) indicates the conjugate relation between belief and plausibility, the $\text{Unc}$ shows the level of uncertainty.

Considering an event in Natech scenarios, we can get belief mass presented by $\mathcal{P}$ and $\bar{\mathcal{P}}$.

$$m(H_1) = \text{Bel}(H_1) = \mathcal{P}(H_1)$$
$$m(H_2) = \text{Bel}(H_2) = \mathcal{P}(H_2)$$
$$m(H_1, H_2) = 1 - (\mathcal{P}(H_1) + \mathcal{P}(H_2))$$
3.3.2. Propagation of belief masses in a BN
Nodes in a cascading disaster chain are binary variables with two states (True or False) in our model. The BN describing a Natech Scenario can be seen as a failure system. We use event symbols, logic gate symbols to describe the causal relationship among various events in the system. The input events of logic gate are the ‘cause’ of output events, and the output event of logic gate is the ‘result’ of input event. According to propagation in a failure system, the input of two focal elements is ‘True’ or ‘False’. A Bayesian network representation can lead to several failure modes [41]. The AND truth table and OR truth table are seen tables 2 and 3. OR gate implies an event occurs as long as at least one of the input events takes place. AND gate implies an event occurs only if all input conditions are met.

Because the assignment of conditional Probability table (CPT) requires exact causality but it is generally difficult to acquire, it is a common practice to build conditional probability tables by using traditional AND/OR logic gates [20]. The CPT is modified for an OR/AND gate to obtain the belief mass propagation. Our inference algorithms propagating uncertainty is based on the more general evidence theory, not on the traditional probability theory.

Figures 7 and 8 show cases in which A and B are connected to C via AND gate and OR gate respectively. For a root node, the CPT contains only a row describing the a priori probability of each state. CPT of a children node is obtained inference algorithms in tables 2 and 3 called conditional belief based on imprecise probability in the network. Table 4 contains the conditional belief table $P(Z|X, Y)$ in the case of AND and OR gates, which explains the failure propagation mechanism. $X$, $Y$ and $Z$ are binary variables with two focal elements $\{H_1\}$, $\{H_2\}$ in the frame of discernment $\Omega$. Table 5 is the relations between the states of nodes in table 1 and focal elements in the frame of discernment $\Omega$.

The diagram represents component failures and how they could cause social-economic system failures. We extend the fault tree analysis method to describe the process of the failure transmission in a social-economic system. Figure 9 is a fault tree translated from figure 6.
4. Data sources and results

4.1. A case study of Guangdong province, China

In this section, we make a case study of Guangdong province, an area prone to natural disasters. Guangdong province is located at the southernmost tip of mainland China. Since much of Guangdong lies south of the Tropic of Cancer, it is one of the Chinese provinces with tropical and subtropical climates. The important position Guangdong takes in China’s booming economy also urges a sound understanding of changes of floods, droughts and typhoon disasters in this region [42]. We use our method to analyze the Natech scenario triggered by typhoon in Guangdong province. The loss will be predicted by the reasoning rules based on evidence theory, which is helpful for finding the key nodes in the disaster chain.

We estimate the prior probability of BN for Natech scenarios through collecting historical data.

4.1.1. The prior probabilities for predictor variables

The probability of typhoon attacking this is $0.10 \leq P(H_t) \leq 0.20$. We can conclude.

\[
\begin{align*}
\text{Bel}(H_t) & = 0.10 \leq P(H_t) \leq 0.20 = PIs(H_t) \\
\text{Bel}(H_d) & = 0.80 \leq P(H_d) \leq 0.90 = PIs(H_d)
\end{align*}
\]

\[m(H_t) = 0.10\]
\[m(H_d) = 0.80\]
\[m(H_t, H_d) = 0.10\]

The value of health technicians per 1,000 people in each province from 2008 to 2018 was collected and ranked in China Statistical Yearbook[^4]. When the rank of health technicians is between 1st and 10st, the local aid resources are relatively abundant; When the rank is between 11st and 20st, the local aid resources are medium; when the rank is below 20st, local aid resources are relatively scarce. So, we conclude that the probability of local aid resources being sufficient is 55 percent, and the probability of resources being medium is 45 percent. That is,

[^4]: [http://www.stats.gov.cn/tjsj/ndsj/2019/indexch.htm](http://www.stats.gov.cn/tjsj/ndsj/2019/indexch.htm)

---

Table 6. Waterlogging, urban utilities network 1 failure, urban utilities network 2 failure’s CPT.

| Natural disaster | Waterlogging | Urban utilities network 1 failure | Urban utilities network 2 failure |
|------------------|--------------|----------------------------------|----------------------------------|
| $H_t$            | 23           | 77                               | 0                                |
| $H_d$            | 0            | 100                              | 0                                |
| $(H_t, H_d)$     | 33           | 34                               | 33                               |

Figure 10. Initial Bayesian network for representing a Natech accident.
Table 7. Assessment of the disaster risk in Guangdong province.

| Name of node       | Serious | Medium | Slight |
|--------------------|---------|--------|--------|
| Economic loss      | 0.04    | 0.05   | 0.91   |
| Environmental pollution | 0.14   | 0.11   | 0.75   |
| Casualties         | 0.08    | 0.06   | 0.86   |

Table 8. Resilience of this area.

| Name of node | Strong | Medium | Weak |
|--------------|--------|--------|------|
| Resilience   | 0.78   | 0.10   | 0.12 |
The probability of the 'local aid resource shortage' being 'true' is 0, the probability that the state being 'false' is 55%, and the probability that the state being 'uncertain' is 45%.

The value of regional professional public health institutions is obtained from the data in the China Health Statistics Yearbook (National Health Commission of the People’s Republic of China 2009 ~ 2019). By ranking the number of provincial institutions, it was found that the number of institutions in Guangdong province kept the top six from 2008 to 2018. That is, the number of emergency aid resources is relatively abundant. Therefore, we conclude that the probability of Emergency aid resources shortage being 'false' is 100%.

4.1.2. Propagation for child nodes
The conditional probability of Waterlogging due to typhoons can be calculated from the data of the China Weather Typhoon Network. The conditional probabilities of the failure of Urban utilities network 1 and Urban utilities network 2 are identified from experts’ experiences. The CPTs of the above nodes are shown in table 6. Other child nodes’ conditional probabilities are propagated via an OR gate or AND gate (rules seen in table 4).

The BN has been run in Netica software to calculate the belief mass of outputs (see figure 10). They are described in table 7. We can induce the Resilience of this city (see table 8) finally.

4.2. Diagnostic analysis
The influential factors were selected for diagnostic analysis. The quantitative causal relationship between influence factors and target variables is obtained by Bayesian network reverse reasoning. Two aspects are considered in the process of a Natech scenario simulation: The natural factor and human factors. We change the
natural factor and human factors in the Natech scenario of Guangdong province separately to predict the losses in the socio-economic system.

### Table 10. Waterlogging, Urban utilities network 1 failure, Urban utilities network 2 failure’s CPT.

| Natural disaster                  | Waterlogging | Urban utilities network 1 failure | Urban utilities network 2 failure |
|-----------------------------------|--------------|-----------------------------------|-----------------------------------|
| True                              | 61           | 75                                | 75                                |
| False                             | 50           | 60                                | 60                                |
| Uncertain                         | 33           | 33                                | 33                                |

### Table 11. Resilience of Guangdong province.

| Resilience                          | False | Uncertain | True | Excepted value | Rate of change |
|-------------------------------------|-------|-----------|------|----------------|----------------|
| Waterlogging                        | 0.911 | 0.033     | 0.056| 2.855          | 69%            |
| Urban utilities network 1 failure  | 0.543 | 0.124     | 0.333| 2.210          | 77%            |
| Urban utilities network 2 failure  | 0.543 | 0.124     | 0.333| 2.210          | 77%            |
| Local aid resources shortage        | 0.550 | 0.450     | 0.000| 2.550          | 78%            |
| Emergency aid resources shortage    | 1.000 | 0.000     | 0.000| 3.000          | 67%            |
| Strong                              | 0.778 | 0.103     | 0.119| 2.659          | 70%            |
| Medium                              | 0.313 | 0.243     | 0.444| 1.869          |                |
| Weak                                |       |           |      |                |                |

* Excepted Resilience is the aggregated value of the three states strong, medium and weak with the probabilities as their weights. We set the value of these three states strong, medium and weak as 3,2,1. The larger the value of excepted resilience is, the greater the ability of the region to resist risk is. Excepted Waterlogging, Urban utilities network 1 failure, Urban utilities network 2 failure, Local aid resources shortage and Emergency aid resources shortage are the aggregated value of the three states false, uncertain and true with the probabilities as their weights. We set the value of these three states false, uncertain and true as 3,2,1.
Case 1. Natural Factor.

This case identifies the effects of natural factor. Set the parameters $m(H_i) = 1$ of Natural hazard, and observe the change of losses. The results are shown in figure 11 and figure 12 shows the belief mass changes before and after the ‘Natural hazard’ changes. We obtain the BN via Netica software (see figure 11).

Case 2. Human factors.

In order to better reflect the influence of human factors, the effects of a same typhoon risk for differently infrastructure cities, case 2 will increase the degree of human factors’ risk by 50%. Set the parameters of human factors in tables 9 and 10 and observe the change of the belief mass of losses. The results are shown in figure 13. Figure 14 shows the belief mass changes before and after the human factors change. We obtain the BN via Netica software (see figure 13).

Under the same natural scenario setting, the severities of Economic loss and Environmental pollution increased, as shown in figure 14. The severities of Casualties have obviously changed. In another hand, the parameters of Resilience also has obviously changed. The Resilience of new city is worse than before. We list the changing rate of the causal relationships between human factors and Resilience (see table 11). The failure of Urban utilities network 1 and Urban utilities network 2 and Local aid resources shortage’s effects on Resilience are reduced, while Waterlogging and Emergency aid resources shortage’s effects on Resilience are expanded. Waterlogging and Emergency aid resources are the key factors if we want to improve urban Resilience.

5. Discussion

If the city managers are not satisfied with the results and think the degree of the three kinds of losses not acceptable, then they need to find a way to find which network parameters should be to modified to lower the degree of three kinds of losses to acceptable levels. This problem can be resolved through sensitivity analysis. This section will analyze the sensitivity from three aspects.

The sensitivity analysis is taken for the BN of Economic loss in initial BN (see figure 10) and the result indicates the influence of natural factor and human factors on Economic loss. The results are expressed as the percentage of variance of beliefs, which can reflect the impact of specific variables on the target variables (see figure 15).
In the aspect of natural factor, the variance of Natural hazard’s belief is 3.17%. In the aspect of human factors, Material_leakage and Traffic confusion have the greatest impact on Economic loss. The percentages of variance of beliefs of these two factors are both 9.31%.

The sensitivity analysis is taken for the BN of Environmental pollution in initial Bayesian network (see figure 10) and the result demonstrate the influence of the natural factor and human factors on Environmental pollution (see figure 16).

In the aspect of natural factor, the variance of Natural hazard’s beliefs is 0.94% compared with Environmental pollution. Natural disasters have less influence on Environmental pollution than Economic loss. Traffic confusion and Material_leakage are the most important factors impacting on Environmental pollution.

Figure 16. Sensitivity to target variable 'Environmental pollution'.

Figure 17. Sensitivity to target variable 'Casualties'.

In the aspect of natural factor, the variance of Natural hazard’s belief is 3.17%. In the aspect of human factors, Material_leakage and Traffic confusion have the greatest impact on Economic loss. The percentages of variance of beliefs of these two factors are both 9.31%.

The sensitivity analysis is taken for the BN of Environmental pollution in initial Bayesian network (see figure 10) and the result demonstrate the influence of the natural factor and human factors on Environmental pollution (see figure 16).

In the aspect of the natural factor, the variance of Natural hazard’s beliefs is 0.94% compared with Environmental pollution. Natural disasters have less influence on Environmental pollution than Economic loss. Traffic confusion and Material_leakage are the most important factors impacting on Environmental pollution.
(3) The sensitivity analysis is taken for the BN of Casualties in Bayesian network to target variables of human factors (see figure 13) and the result indicated the influence of the natural factor and human factors on Casualties (see figure 17).

In the aspect of the natural factor, the variance of the natural hazard’s beliefs is 1.33% compared with Casualties. In the aspect of Human factors, Epidemic has the greatest impact on Casualties.

6. Conclusions

The study provides an integrated scenario assessment approach combining BN and evidence theory to deal with Natech accidents. In the case of diagnostic analysis and sensitivity analysis, we can find the quantitative causal relationship between influence factors and target variables and predict the losses in the socio-economic system. Our method can support policymakers in making decisions, and protect people from the impacts of cascading disasters.

However, the form of imprecise probabilities in our model that describes the probabilities of original states of a Natech accident is relatively simple. We could extend our model with other forms of imprecise probability. Inference algorithms to compute the belief mass propagation in a BN also need to be modified to deal with new forms of imprecise probability.

Another limitation is the rules designed to manipulate imprecision probabilities. Our model simplified the complex faulty propagation to two logical units, AND and OR gates. Although traditional categorical logic can be used to represent and assess many of our most common patterns of reasoning, Natech accidents need much more comprehensive and powerful logical languages for expressing rational thought. Enriching reason rules will be one of the research directions in the future.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (NSFC) (71871121), Future Network Scientific Research Fund Project (FNSRFP-2021-YB-19), and Project of meteorological industry research center (sk20210032).

Data availability statement

No new data were created or analysed in this study.

Ethical statement

There are no human participants or animal experimentation.

Conflict of interest

The authors declare no conflict of interest.

ORCID iDs

Mei Cai @ https://orcid.org/0000-0001-9648-0878

References

[1] Cruz A M and Suarez-Paba M C 2019 Advances in natech research: an overview Progress in Disaster Science 1100013
[2] Steinberg I, I., Sengul H and Cruz A M 2008 Natech risk and management: an assessment of the state of the art Nat. Hazards 46 143–52
[3] Mesa-Gómez A, Casal J and Muñoz F 2020 Risk analysis in Natech events: state of the art J. Loss Prev. Process Ind. 64 104071
[4] Girgin S and Krausma E 2012 Rapid natech risk assessment and mapping tool for earthquakes: rapid-n Chemical Engineering Transactions (CET Journal) 26 949–60
[5] Krausmann E, Girgin S and Necci A 2019 Natural hazard impacts on industry and critical infrastructure: natech risk drivers and risk management performance indicators Int. J. Disaster Risk Reduct. 40 101163
[6] Suarez-Paba M C, Cruz A M and Muñoz F 2020 Emerging natech risk management in colombia: a survey of governmental organizations Saf. Sci. 128 104777
[7] Cozzani V et al 2014 Quantitative assessment of domino and NaTech scenarios in complex industrial areas J. Loss Prev. Process Ind. 28 10–22
[8] Girgin S, Necci A and Krausmann E 2019 Dealing with cascading multi-hazard risks in national risk assessment: the case of natech accidents Int. J. Disaster Risk Reduct. 35 1–13
[9] IAEA 2015 The Fukushima Daiichi accident—report by the director general (Vienna: IAEA Press)
[10] Pescaroli G and Alexander D 2015 A definition of cascading disasters and cascading effects: going beyond the ‘toppling dominos’ metaphor Planet@Risk 3 58–67 (http://discovery.ucl.ac.uk/1465510/)
[11] Alexander D and Pescaroli G 2019 What are cascading disasters? UCL Open Environment. 1 1–6
[12] Rahman H A, Beznosov K and Marti J R 2009 Identification of sources of failures and their propagation in critical infrastructures from 12 years of public failure reports Int. J. Crit. Infrastruct. 5 220–44
[13] Huang K X et al 2020 An innovative quantitative analysis methodology for Natech events triggered by earthquakes in chemical tank farms Saf. Sci. 128 104744
[14] Pescaroli G 2018 Understanding and mitigating cascading crises in the global interconnected system Int. J. Disaster Risk Reduct. 30 159–63
[15] May F 2007 Cascading Disaster Models in Postburn Flash Flood 443–64
[16] Guo X X et al 2020 Fuzzy Bayesian network based on an improved similarity aggregation method for risk assessment of storage tank accident Process Safety and Environmental Protection 144 242–53
[17] Zhang J et al 2020 Bayesian network-based risk assessment of single-phase grounding accidents of power transmission lines International Journal of Environmental Research and Public Health 17 1841
[18] Kumru M and Kumru P Y 2013 Fuzzy FMEA application to improve purchasing process in a public hospital Appl. Soft Comput. 13 721–33
[19] Khakzad N 2019 System safety assessment under epistemic uncertainty: using imprecise probabilities in Bayesian network Saf. Sci. 116 149–60
[20] Zarei E et al 2019 Safety analysis of process systems using fuzzy bayesian network (FBN) J. Loss Prev. Process Ind. 57 7–16
[21] Kendall A and Gal Y 2017 What uncertainties do we need in bayesian deep learning for computer vision? NIPS 1–12
[22] He K et al 2016 Deep residual learning for image recognition IEEE Conference on Computer Vision and Pattern Recognition abs/1512 03385
[23] Griffiths R R et al 2022 Achieving robustness to aleatoric uncertainty with heteroscedastic Bayesian optimisation Machine Learning: Science and Technology 3 1–24
[24] Shafer G 1976 A Mathematical Theory of Evidence (Princeton: Princeton University Press) (https://doi.org/10.2307/1268172)
[25] Simon C, Weber P and Esvuokff A 2007 Bayesian networks inference algorithm to implement dempster Shafer theory in reliability analysis Reliability Engineering and System Safety 93 950–63
[26] Zhang X G, Mahadevan S and Deng X Y 2017 Reliability analysis with linguistic data: an evidential network approach Reliability Engineering and System Safety 162 111–21
[27] Guo K H and Li W L 2011 Combination rule of D–S evidence theory based on the strategy of cross merging between evidences Expert Syst. Appl. 38 13360–6
[28] Smith E D et al 2007 Sensitivity analysis, a powerful system validation technique The Open Cybernetics & Systemics Journal 2 39–56
[29] Chen N and Shi X M 2021 Research on public haze sensitivity difference based on factor analysis and cluster Analysis: A Case of Xi’an City. Area Research and Development 40 156–61
[30] Guan J et al 2020 Analysis on the economic value and its sensitivity of Larix gmelini carbon sequestration afforestation project based on the B-S option pricing theory Journal of Arid Land Resources and Environment 34 63–70
[31] Lv Y, Fan X Y and Wu H N 2021 Sensitivity analysis of factors influencing carbon prices in china Soft Science 35 123–30
[32] Sun K 2021 The sensitivity analysis on the influence factors of the regional innovation capability in china: based on the spatial econometric methods Journal of Applied Statistics and Management 40 417–28
[33] Tan Y F et al 2019 Dynamic response of grain production and cultivated land quantity change in jiangsu province based on sensitivity Analysis. Resources and Environment in the Yangtze Basin 28 1102–10
[34] Huang H et al 2021 The mechanism and sensitivity analysis of soil freeze-thaw erosion on slope in eastern Tibet Acta Geographica Sinica 76 87–100
[35] Li F et al 2018 Ecological sensitivity analysis based on urban environmental quality zoning index method: a case study of jingmen city Urban Development Studies 25 21–8
[36] Liu S Y et al 2021 Conservation of scenic resources in national parks based on ecological sensitivity assessment and landscape pattern analysis: a case study of shennongia national park in hubei province Areal Research and Development 40 161–7
[37] Gong Z W et al 2020 Cascading disasters risk modeling based on linear uncertainty distributions Int. J. Disaster Risk Reduct. 43 101385
[38] Francesco P et al 2020 Multi-hazard assessment of bridges in case of hazard chain: state of play and application to vehicle-pier collision followed by fire Frontiers in Built Environment 6 1–19
[39] Puga J L, Kryziwinski M and Altman N 2015 Bayesian networks Nat. Methods 12 799–800
[40] Rakowsky U K 2007 Fundamentals of the Dempster–Shafer theroy and its applications to reliability modeling Int. J. Reliab. Qual. Saf. Eng. 14 579–601
[41] Simon C, Weber P and Esvuokff A 2008 Bayesian networks inference algorithm to implement Dempster Shafer theory in reliability analysis Reliab. Eng. Syst. Saf. 93 950–63
[42] Zhang Q et al 2011 Flood, drought and typhoon disasters during the last half-century in the Guangdong province, China Nat. Hazards 57 267–78