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A Bayesian Network Model for Rough Estimations of Casualties by Strong Earthquakes in Emergency Mode

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Abstract. Rough estimations in emergency mode are now playing an important role in making key decisions for managing disasters including search and rescue. Most of the studies only paid attention to the earthquakes and ignored the presence of disaster chains and the hazard interactions in earthquakes. Bayesian Networks are ideal tools to explore the causal relationships between events, combine prior knowledge and observed data, and are integrated to solve uncertain problems. In such situations, we present improvements based on a Bayesian Network Model in approaches to estimations of casualties in earthquakes. According to the development of the earthquake disaster chain in literature, the proposed model extracts the key events of earthquakes, considers the hazard interactions, and constructs the Bayesian Networks based on a scenario-based method, to deal with the events in the earthquakes. In the model, lifeline system damages, fires, landslides, and debris flow have been integrated into the networks. The conditional probability tables are encoded by using the collected cases. Validations in the Netica allow the simulation of expected shaking intensity and estimation of the expected casualties by strong earthquakes in emergency mode. Compared to the literature, the method is closer to the fact in the rough estimations, providing important information for our response to earthquakes. Further, rough estimations are started when only seismic intensity or fewer earthquake source parameters are available.

Keywords: rough estimations, Bayesian Networks, earthquake, emergency mode

1 Introduction

Compared to other disasters, the earthquake is a kind of natural disaster with unpredictability, great randomness, great destructive power, and prone to cause other secondary disasters including fires, explosions, gas leaks, landslides and debris flows [1]. In those secondary disasters, fires, landslides and debris flows are the leading risk factor for death. Humans have experienced lots of extremely unpredictable and destructive earthquakes in the last decades. The earthquakes made us experience numerous and expensive losses or casualties. In China, the Tangshan earthquake of 28 July 1976, the Xingtai earthquake of 8 March 1966, Wenchuan earthquake of 12 May 2008 were the nation's three most costly earthquakes since 1949. Timely and adequate action just after an event can result in significant benefits in saving lives and prompt rehabilitation phases. Information about possible damage and the expected number of casualties is very critical for deciding on search and rescue operations, as well as offering humanitarian assistance [2]. Accurate response level requires a lot of basic information, such as earthquake occurrence time, intensity, population density, geology, personnel distribution, and regional housing basic data. Due to the rapid development of the city and the untimely collection of risk census data, it is difficult for the government to grasp all kinds of information required for the preliminary judgment of the disaster at the first time, and can not timely obtain the personnel and property losses caused by the earthquake, which leads to some difficulties in the response work after the earthquake. Estimating losses is essential to decision-making at all levels of government. The estimations provide a basis for developing mitigation plans and policies, emergency preparedness, and response and recovery planning.

After such a disaster, a rough damage estimation is necessary for the disaster management agency [3]. In the literature of post-earthquake damage estimations, researchers focus on direct economic losses and casualties. The former includes damage to buildings and other engineering structures, facilities, equipment, and goods destroyed by the earthquake. The method of estimations is complex and time-consuming. Usually, it would take a lot of time to estimate the direct economic losses after the earthquakes. In terms of time and access, the latter has great advantages. For the rough estimations after earthquakes, the general casualties are generally regarded as an important research direction. Researchers have carried out a great deal of research on the casualties after the earthquake.

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Most of these researchers focused on the contributions of seismic parameters or buildings on fatalities. Disaster chains and hazard interactions were neglected by most researchers. There is a relationship between these seemingly complex and disordered events. Bayesian networks (BNs) are ideal for taking the earthquake event set that occurred, predicting the likelihood of casualties, fires, lifeline system damages, landslide and debris flows, and assisting governments in determining the rescue operations.

2 Literature Survey

Previous research for estimating the casualties caused by the earthquake can be divided into the method of empirical functions and buildings' damage [4].

As the first proposed method, researchers tried to establish the relationship between earthquake parameters and the number of casualties reported from historical data. The empirical statistical approach is widely used. In the approach, the magnitude, intensity, focal depth, and population density of an earthquake are taken as parameters, and the regression is carried out by using mathematical tools. Frequently used parameters include magnitude, intensity, focal depth, population density, gross domestic product, poverty, health status, traffic, population density, and time of the earthquake [5]. Badal summarized the human loss caused by the strong earthquakes worldwide in the 20th century and proposed a model consisting of a correlation between the number of casualties and the earthquake magnitude as a function of population density [6]. Jaiswal analyzed the earthquake death rate worldwide, developed an empirical fatality model based on the Prompt Assessment of Global Earthquakes for Response system of the United States Geological Survey (USGS). The model divided the area of people exposed to earthquakes into shaking intensity levels and estimated the fatality by multiplying them by the fatality rates for that level [7]. Liu analyzed the fatal earthquakes that occurred in mainland China from 1949 to 2008 and established classification and discrimination rules for earthquake emergency response levels based on earthquake-related information such as magnitude and population density in the earthquake area [8]. GUL established an artificial neural network model for earthquake casualty prediction using earthquake occurrence time, earthquake magnitude, and population density as predictors, and trained with the samples of 21Mw>5 earthquakes that occurred in Turkey since 1975. He also tested quake-prone areas with models that generated estimates of the number of people expected to be injured [9].

In the other method, the researchers focused on the relationship between the damage of buildings and casualties. Usually, damage indexes are used to measure the impact of buildings on assessment. Considering the influence of building structure, Guettiche made use of the damage, magnitude, and intensity of buildings as parameters to predict economic losses and casualties based on the data of 65 earthquakes in the Mediterranean region from 1900 to 2015 [10]. To extract the textures of buildings and determine the damage level of the building, Ranjbar adopted remote sensing technology and a geographic information system in the constructed model. Then, the model estimates the number of casualties based on the damage level of the building combined with the structural materials of each building, the population residing in each building, the time of the earthquake, and the percentage of damage [11]. Noh proposed a Bayesian statistical framework to combine expert opinions, post-earthquake survey or analysis and simulated data to estimate the fatality. The researchers tested the distribution of the earthquake mortality data obtained from the 2005 Pakistan earthquake and PAGER system and determined that the Bernoulli gamma model is the most suitable for Pakistan seismic data [12]. In Feng's model, the damage degree of the building is evaluated by the damage index (damage index, DI) of the building and the numerical damage model derived from the SRS image. The joint casualty index (joint casualty index, JCI) and the injured person are calculated by combining DI with the material and structure index of the building and using the information of the local geographic information system (geographic information system, GIS) [13].

Due to the lack of detailed knowledge of the building stocks in many areas of the world and inadequate knowledge of the fatality rate given building collapse, the method is not attractive even though it performed much better. Much effort has been focused on the relationship between earthquake parameters and the number of casualties. In natural disaster prevention and response, Bayesian Networks (BNs) can learn the causal relationships between events to understand the problem domain and predict the consequences of intervention. Due to its' remarkable results, BNs have been used to deal with the occurrence and development process of emergencies, model and analyze the whole occurrence and development of emergencies. Ma and Zhang respectively introduced a conceptual framework based on Bayesian networks to analyze and verify earthquake disasters and emergency management measures [14-15].

The remainder is arranged as follows. The construction of the BNs and the data collected are described in Section 3. The simulations are conducted in Section 4. Some conclusions are summarized and remarks are made in Section 5.

3 BNs Modeling

BNs are composed of Bayesian structure and Bayesian parameters. The bayesian structure is a graph of the directed acyclic graph describing the correlation between nodes. Bayesian parameters are a set of parameters based on the conditional probability distribution of each node in the graph. The bayesian structure consists of nodes that represent variables and edges representing dependencies between nodes. Each directly connected node displays a dependency. In earthquakes, various events interact with each other to form a Bayesian network. The events are considered nodes [16]. Simulation software Netica was used and the flow chart was presented in Fig. 1, which shows the model framework of BNs for casualty estimation. The casualty estimation includes the phases of data collection, factor selection, data normalization on the nodes, and simulations through Netica.

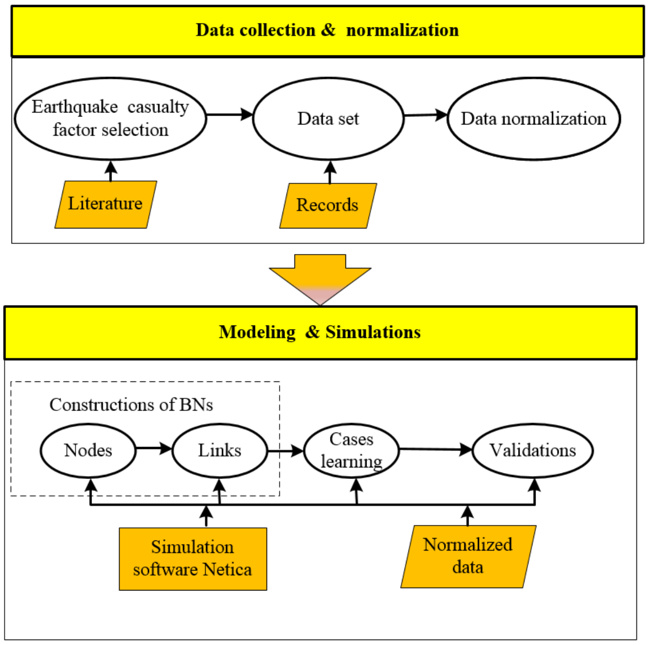


Fig. 1. Model framework for casualty estimation

3.1 Probabilistic Reasoning of BNs

There are relationships between events. In Fig. 2, nodes A and B are called the parent node of node C.

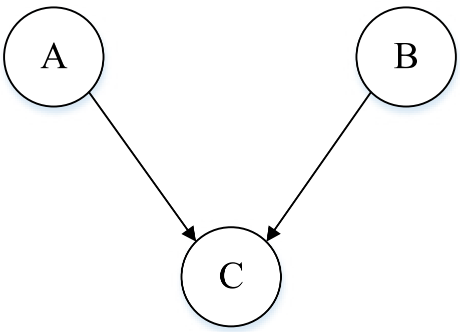


Fig. 2. Type of head-to-head in BNs

For events A and B, provided that event C is an unknown, we deduce that

$$P(A,B,C) = P(A) * P(B) * P(C / A,B) \tag{1}$$

Where P (A, B, C) is the probability that A, B, and C are true at the same time. P(C/ A, B) is the probability that events A and B are true and that C occurs.

In Fig. 3, C is referred to as the parent node of A and B.

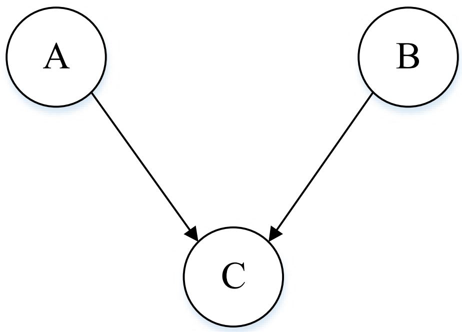


Fig. 3. Type of tail-to-tail in BNs

If nodes A and B are independent of each other, we deduce that

$$P(A,B / C) = P(A,B,C) / P(C) \ . \tag{2}$$

Where P(A, B/ C) is the probability of both events A and B occurring given that C is true.

In the constructed network, each event may have parent and child nodes. If parent node A and child node B have events A1, A2, Ak and B1, B2, Bm respectively, we can derive the conditional probabilities.

$$P(Ai / B) = P(Ai, B) / \sum_{i=1}^{k} P(Ai) P(B / Ai) \ . \tag{3}$$

Where P(Ai), the prior, represents the probability of event Ai. P(Ai, B) is the probability of both Ai and B being true. P(B/Ai) is the probability of event B occurring given that Ai is true.

$$P(Bj) = \sum_{i=1}^{m} P(Ai) P(Bj / Ai) \ . \tag{4}$$

Where P(Ai) and P(Bj) respectively represent the probability of event Ai and Bj. P(Bj/Ai) is the probability of event Bj occurring given that Ai is true.

3.2 Influence Factors

By reviewing the literature, we found that the consequences of earthquakes depend on seismic intensity, the time of occurrence, the exposed population, occupation index, construction quality, and other factors. The most important risk factors for earthquake-induced casualties include the degree of damage, type of the building, and occupation index. The other important risk factors are the location of the person inside the building, his mobility within the house during the shaking, and the hour of the event. Some factors are considered which are available just after the strong earthquakes. According to the research in literature, we select seismic intensity, occurrence time, population density, secondary disasters, building seismic performance, casualties and anti-seismic capacity of buildings as network nodes in Table 1 [17-19].

Table 1. The specific information of each node in BNs

Code	Node	State
I	Seismic intensity	I ≤ 7; I =8; I =9; I ≥ 10
T	Time of occurrence	1 am to 6 am; 6 am to 9 am 9 am to 8 pm; 8 pm to 1 am
D	Population density (per Km^2)	P ≥200 P < 200
B	Building seismic performance	Over one degree higher than seismic or meets seismic fortification intensity Below seismic fortification intensity
L	Lifeline system damage	Damaged but recovered quickly Paralyzed for a long time
M	Building damage	Partially destroyed Massively destroyed Almost destroyed
F	Fire	No fires or few fires on a small scale Large number or scale of fires
A	Landslide and debris flow	Did not occur Serious consequences
C	Casualties	N≥300; 300>N≥50; 50>N≥10; N<10

3.3 Constructions of BNs

BNs are composed of Bayesian structure and Bayesian parameters. The bayesian structure is a graph of the directed acyclic graph describing the correlation between nodes. Bayesian parameters are a set of parameters based on the conditional probability distribution of each node in the graph. The bayesian structure consists of nodes that represent variables and edges representing dependencies between nodes. Each directly connected node displays a dependency. In earthquakes, various events interact with each other to form a Bayesian network. The events are considered nodes.

The event set is created by studying the happened earthquakes and constructing the scenarios. The process of creation is very important to analyze the networks. Focusing on the impact of earthquake disasters on the death of people, we make use of earthquake intensity, time, population density, house collapse as input. Also, house collapses, fire disasters, communication interruptions, road damages are taken as the state of the system, and casualties are the output of the system. As usual, all the events were discretized.

By using the nodes described above, we collected the events of earthquakes, extracted the key events of earthquakes, and established the Bayesian Network depicted in Fig. 4.

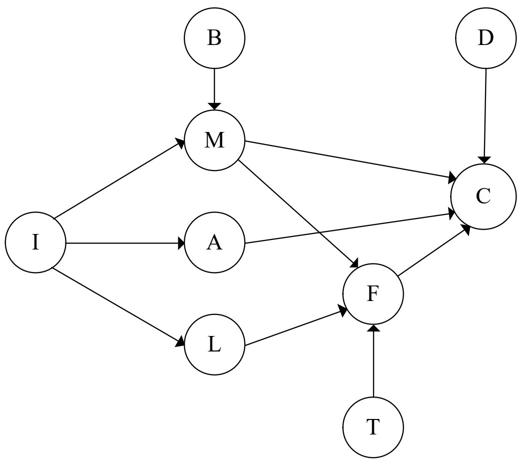


Fig. 4. Networks of earthquake disasters

3.4 Data Sources

The data were taken from statistical documents and literature. Regarding the quality of the provided data, we used various sources of information as follows: (1) China Earthquake Disaster Loss Compilation:1966-1989. (2) China Earthquake Disaster Loss Compilation:1996-2000. (3) China Earthquake Disaster Loss Compilation: 2001-2005. (4) China Earthquake Disaster Loss Compilation: 2006-2010. (5) Disaster Assessment Report including 2011, 2012, 2013, and 2014. (6) National census data. (7) data collected from the internet. (8) others. Referring to the relevant literature of the government and some scholars on the statistics of earthquake casualties, the historical earthquake data of 26 events from 1996 to 2008 were obtained. A database was constructed with all the related information: earthquake parameters (time of occurrence, intensity, magnitude), casualties, building damage ratio, occupation index, construction quality, and others.

4 Simulations

4.1 Netica

Netica is a powerful, easy-to-use, complete program for working with belief networks and influence diagrams. It has an intuitive and smooth user interface for drawing the networks, and the relationships between variables could be entered as individual probabilities, in the form of equations, or learned from data files. It is suitable for applications in the areas of prediction, decision analysis, probabilistic modeling, risk management, expert system building, reliability analysis, and certain kinds of statistical analysis and data mining.

In the section, we use Netica to draw the networks, quantitatively learn the relationships from data files, and generate customizable reports on many aspects of BNs, nodes, states, CPTs, cases, findings, beliefs, sensitivity results and other inference results.

4.2 Conditional Probabilities

According to equation 3, conditional probabilities are calculated by Netica. Some results were shown in Table 2. In the networks, the number of studies cases has a significant impact on the results. If the node did not exist, we assume that all the probabilities are the same.

Table 2. Conditional probabilities of node A

Node A	$I \leq 7$	$I = 8$	$I = 9$	$I \geq 10$
Did not occur	80.0 %	33.3 %	11.1 %	12.5%
Serious consequences	20.0 %	66.7 %	88.9 %	87.5%

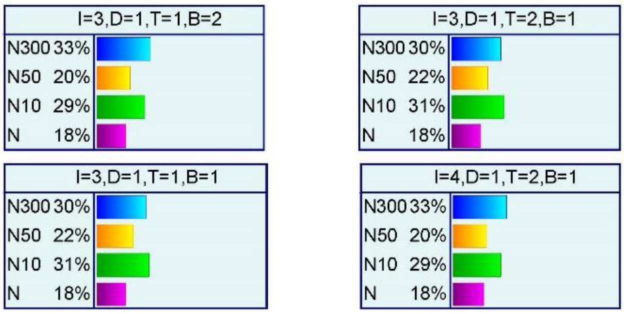
4.3 Validations

In the validations, Netica was used to conduct the simulations. Loss estimations are started as soon as input data (earthquake source parameters) are available. The assumed parameters mainly include seismic intensity, the time of occurrence, population density, earthquake resistance of buildings, and the damage state of buildings. By entering one of the parameters, the damages of earthquakes are derived and calculated. These were also estimated by the BNs and the method in the literature. Table 3 shows that the derived results are more close to the expected results. In all but two of the three cases where there is a miscarriage of the estimation, the death toll was raised by a small margin. At present, the earthquake caused human casualties and losses are also more and more. The higher death toll can effectively reduce the loss of life caused by earthquake disasters.

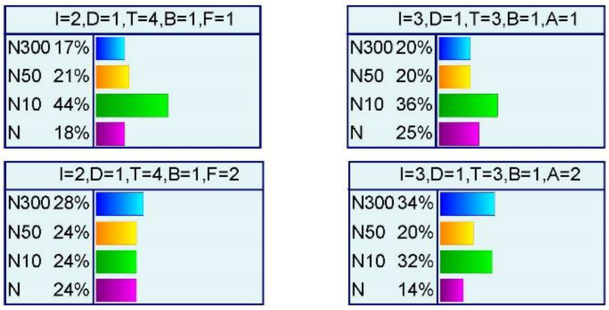
Table 3. Simulation results

Expected Results	Expected Number	Correct Rate in literature 8	Correct Rate in Proposed Method
I	10	90.00 %	100.00 %
II	2	0.00 %	50.00%
III	11	81.82 %	90.91 %
IV	3	33.33 %	66.67 %

Fig. 5 shows that building seismic performance and intensity contribute significantly to the results of loss simulations. For the reason that the high intensity makes more buildings collapse in the earthquakes, more people will be trapped in the building and lead to death. If all the buildings were constructed to withstand the shaking, fewer people will be suffered. In the simulations, there is a difference in the casualties between regions of the province, though with the same other factors except for the construction typology. Recently, researchers have increasingly focused on traditional buildings, such as wooden houses in Yunnan Province, having an advantage in resisting seismic shaking. The traditional construction typology performed much better in the Jinggu earthquake and Ludian earthquake of 2014 [20]. Among the 26 cases, most of them involved the western part of China caused a large number of casualties. The death caused by the earthquake has a lot to do with the location of the constructions. Many of these areas of casualties are prone to geological disasters. The case suggests that the government should strengthen the construction and location management of residential areas. As secondary disasters, fire or landslide and debris flow have a very important impact on earthquake disasters. In Fig. 5(c), they show that it will lead to greater losses and casualties if a fire exists. This is also applicable to landslide and debris flow.



(a) Building seismic performance (b) Seismic intensity



(c) Fires (d) Landslide and debris flow

Fig. 5. Influences of some nodes in BNs

5 Conclusions

We give the description of Bayesian networks models for rough estimations in earthquakes, construct the Bayesian networks applying a scenario-based method, calculate the conditional probabilities through the collected cases, and analyze the seismic vulnerability of different earthquakes at risk, as well as a methodological method for risk assessment. The examples of the proposed application for damage and casualties assessment in emergency mode, as well as a comparison of the data in the literature, are given. On the whole, the proposed method applying the bayesian networks for expected loss and risk assessment showed some benefits to the previous calculations. The proposed method provides important information for region-based earthquakes preparedness. Further, rough estimations are started when fewer earthquake source parameters are available. In the future, more cases should be collected to avoid existing limitations in simulation models and nodes on the responses during the earthquakes. We believe that more efforts will be made to enhance more accurate personnel and property losses caused by the earthquake in the earthquakes.

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