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A Deep Belief Network and Case Reasoning Based Decision Model for Emergency Rescue

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Abstract

The frequent occurrence of major public emergencies in China has caused significant human and economic losses. To carry out successful rescue operations in such emergencies, decisions need to be made as efficiently as possible. Using earthquakes as an example of a public emergency, this paper combines the Deep Belief Network (DBN) and Case-Based Reasoning (CBR) models to improve the case representation and case retrieval steps in the decision-making process, then designs and constructs a decision-making model. The validity of the model is then verified by an example. The results of this study can be applied to maximize the efficiency of emergency rescue decisions.

Keywords: deep belief network, case-based reasoning, decision support, emergency rescue, earthquake.

1 Introduction

With the rapid development of the times today, the society is also suffering from all sides of the test. As small as daily life, such as carbon dioxide emissions from automobiles [7], to various disaster events such as chemical enterprises' production pollution [13], earthquakes [17], etc., will cause great harm to the environment on which we live. This paper takes an earthquake as a context for studying

emergency rescues. An earthquake can endanger human life and property and can have significant social, economic, political, and environmental impacts. Decision-making guiding the emergency response should therefore be as efficient as possible. Research shows many studies of emergency responses to earthquakes, but most of them are text-based. Moreover, there are still errors made in emergency rescuing, mainly due to inaccurate decision-making systems.

To solve this problem, this paper mainly uses the Deep Belief Network (DBN) and Case-Based Reasoning (CBR) models to construct an earthquake emergency rescue decision-making [9, 21] model. First, a large number of text-based cases are normalized and then case retrieval is performed to match the cases with the highest similarity [19, 23]. And last, this paper applies the case study [11, 15] to verify the model. The earthquake emergency rescue decision-making model constructed in this paper improves the existing decision-making reasoning method and expands its applicability and feasibility.

2 Literature review

Deep Belief Network (DBN) is a probability generation model developed by bioneural networks and shallow neural networks to infer the distribution of data samples from joint probability distributions [14].

The DBN model generates data based on maximum probability by training the weights of neurons in the network structure, forming high-level abstract features, and improving the classification performance of the model. It is considered a good method for knowledge representation and uncertainty reasoning, and its application is a hot topic in data mining. Yushi Chen *et al.* applied DBN to the classification of hyperspectral data and improved its accuracy [4]. Takashi Kuremoto *et al.* applied DBN to forecasting the time series and proved the forecasting accuracy. And they pointed out that the model proposed can be applied to the approximating and short-term prediction of chaotic time series [12]. Oriol Vinyals *et al.* applied DBN to the speech recognition task under mismatched noise conditions, and proved that DBN was better than MLP under the clean condition [20]. Walter H. L. Pinaya *et al.* applied DBN to characterize differences in brain morphometry in schizophrenia and proved that DBN was more accurate than SVM [16]. A. Deoras *et al.* applied DBN to the semantic tagging which was a sequence classification task. And they proved the model had improved generalization capability especially when some features were missing or noisy [5]. Yan Gao *et al.* applied the DBN algorithm to the problem of the performance prediction of cloud service, and proved its effectiveness by experiment [8]. Jinsheng Yang *et al.* constructed a Wireless Local Area Network (WLAN) fingerprint location database with an improved DBN algorithm [22]. These studies show that the DBN algorithm is effective in solving the problem of data loss in data mining.

Case-Based Reasoning (CBR) simulates the process of learning from previous incidents to solve current problems. Case experience obtained according to CBR semantics can be readily applied to the target case. CBR can prevent the repetition of past errors and accelerate the learning process by adding case correction and case reasoning to the case base. Jaeseok Huh *et al.* applied the CBR algorithm to the travel routes for large-scale AS/RSs and proved the method proposed made travel routes optimized quickly [10]. Petr Berka introduced that how the CBR approach can be used for sentiment analysis[2]. Jiyong Ding *et al.* applied the improved CBR algorithm to the predictions of project performance, then took Nanjing HF project as an example, and proved the innovation of the method [6]. D. A. Adeniyi *et al.* proposed the Chi-square case-based reasoning model and applied it to the realization of an automated risk calculator and death prediction, and then proved the precision rate and predictive quality [1]. Chanvarasuth *et al.* applied the CBR algorithm to investment decisions, solved the choice of optimal future investment, and proved the method was superior to the traditional method by experiment [3]. Michael Schnell *et al.* applied the CBR algorithm to make the medical coding practices and a short evaluation more easily [18].

In summary, DBN can retain the characteristics of sample attributes, adapt dynamic data to a large extent, and solve the problem of data deletion. The CBR algorithm is suitable for handling cases with high repetition, and through case reuse and correction, can improve the existing case library, widely used in decision support. Therefore, this paper combines with the improved DBN algorithm and uses CBR technology to design an earthquake emergency rescue decision model, aiming to improve

the reliability and accuracy of emergency rescue decision-making and improve the applicability and feasibility of the decision-making model in an earthquake disaster.

3   Decision model of earthquake emergency rescue based on DBN-CBR

3.1   Analysis of earthquake emergency rescue decision

3.1.1   Analysis of the constituent elements of earthquake emergency rescue decision

By analyzing the history of earthquakes, the main causes of human fatalities due to earthquakes can be classified into three categories: building collapse, secondary disasters, and social environment effects. The level of destruction resulting from an earthquake is related not only to the seismic characteristics of the earthquake itself, but to such things as the seismic capacity of local buildings and local population density as well as secondary disasters like floods and fires. Thus, the factors influencing earthquake destructiveness can be classified into three categories: earthquake characteristics, natural environment and social environment.

1. Earthquake characteristics

(1) *Magnitude*

Earthquake magnitude is a direct measure of earthquake strength: the higher the magnitude, the greater the energy released by the earthquake and the stronger its destructive force. In general, the direct economic loss produced by the earthquake will increase with the level of its magnitude.

Table 1: Comparison of Direct Economic Loss and Capital Demand for Reconstruction of China's Post-2008 Earthquake Disaster

Earthquake name	Earthquake magnitude	Direct economic losses /$100 million	Estimated funding requirements for reconstruction /$100 million	Completion time for rehabilitation /years	Requirement/Loss ratio
2008 Wenchuan	8.0	8523.09	10000.00	3	1.17
2010 Yushu	7.1	228.47	320.00	3	1.40
2013 Lushan	7.0	665.14	860.00	3	1.29
2014 Ludian	6.5	198.49	270.00	3	1.36
2017 Jiuzhaigou	7.0		118.00	3	

Table 1 demonstrates that the destructive force of the earthquake increases with its magnitude. This is especially clear when we note that the direct economic loss from the Wenchuan earthquake (Magnitude 8.0) is 37.3 times that of the Yushu earthquake (Magnitude 7.1).

(2)*Intensity*

Earthquake intensity is the degree of influence of the earthquake on the surface and the building engineering. In general, the higher the intensity of an earthquake, the greater the damage to local buildings, the higher and faster the building collapse rate, and the less likely people will be able to

escape from the disaster site, leading to an increase in the number of casualties.

(3)*Focal depth*

Focal depth refers to the vertical distance from the earthquake source to the surface. The three focal depth categories are shallow, middle and deep source earthquakes. Shallow source earthquakes with a depth of less than 70 km account for more than 90% of all measured earthquakes globally. So far, the greatest depth measured of an earthquake source is 720 km. For earthquakes of similar magnitude, the focal depth determines the earthquake's intensity and thus indirectly determines its damage intensity. Because the energy released by the earthquake is constantly attenuated in the process of propagation, the deeper the earthquake source, the lower its effect on the surface and its damage intensity; conversely, the shallower the source, the higher the earthquake intensity and its destructiveness.

(4) *Earthquake time*

The time when the earthquake occurs directly affects the number of people inside buildings and their ability to respond, such as if the earthquake strikes late at night when most people are sleeping indoors. Often, nighttime earthquakes cause more casualties and damage than those occur during the day.

2. Natural environment

(1) *Physical characteristics*

The physical characteristics of the earthquake zone has a major effect on the destructiveness of the earthquake. Search and rescue work in a mountainous region can be very difficult and can be further hampered by secondary hazards such as landslides.

(2) *Weather*

Weather conditions such as rain, heat, cold and wind after an earthquake affect the launch of rescue work and the survival rate of people who are buried or injured and can lead to further losses.

(3) *Secondary disasters*

Secondary disasters are disasters caused by earthquake damage, such as fires, floods, explosions, contamination of air and water, landslides, etc. For example, the 1906 San Francisco earthquake ruptured gas pipelines, leading to further casualties and property damage. In 2008, after the Wenchuan earthquake, landslides and other secondary disasters killed tens of thousands of people or about 14.4 percent of the total number of deaths attributed to the earthquake.

3. Social environment

(1) *Population density*

Population density mainly includes two aspects: the number of people indoors and the population density in the earthquake area. When other conditions are the same, the higher the population density, the higher the number of casualties caused by the earthquake, and vice versa.

(2) *Seismic performance of buildings*

The seismic performance of buildings and their fortification ability are related to the strictness of the local building construction standards. The better the seismic performance of buildings, the lower the building collapse rate and speed, and the less the economic losses and casualties caused by the earthquake.

(3) *People indoors or outdoors*

The more people there are indoors when an earthquake occurs, the more the casualties. Conversely, if more people are outside in an open area at the time of the earthquake, the number of casualties will be lower.

(4) *Building collapse rate*

Casualties caused by an earthquake are directly proportional to the building collapse rate.

(5) *Capability and rapidity of regional emergency rescue*

The 72-hour golden law of life-saving shows that the earlier the start of rescue operations, the more people can be saved. Rescue teams in the affected region and the organizations and government authorities behind them therefore need to maximize their planning and implementation speed. In addition, the better a rescue team's ability, the greater the number of people saved.

(6) *Material reserves*

If there are enough material reserves in the place where the earthquake has occurred, the transportation of materials can be appropriately reduced during emergency rescue, which can also avoid the waste of materials. But if there is very little material reserves in the area, a lot of materials will be needed after the earthquake, which must be considered in emergency rescue. From the above analysis, we can conclude the earthquake emergency rescue decision-making factor table, as shown in Table 2.

Table 2: Decision factors for earthquake emergency rescue

Classification	Decision-making factors
Earthquake characteristics	magnitude
	intensity
	focal depth
	earthquake time
Natural environment	physical characteristics
	weather
	secondary disasters
Social environment	population density
	seismic performance of buildings
	people indoors or outdoors
	building collapse rate
	capability and rapidity of emergency rescue
	material reserves

3.1.2 Analysis of decision process of earthquake emergency rescues

To respond quickly after an earthquake, every step in the decision-making process of emergency rescuing should be analyzed in detail. From a macro point of view, this process is circular and the target requiring a decision changes according to the rescue situation. After completing all of the rescue mission, a new command center should be set up, and the aid construction activities will be carried out. Then the new decision-making objectives will be determined according to the new scene situation.

The crisis caused by an earthquake occurs suddenly, but its scope and extent lasts a long time. The emergency decision-making process for earthquake disasters is shown in Figure 1.

After receiving the disaster information of the earthquake scene, the command center, the government function department and the transfer advisory body will make the decision target according to the emergency and corresponding decision plan. Optimal plans will be identified and implemented through analysis and evaluation of multiple groups of procedures. After the rescue, those organizations will judge whether the meeting meets the decision goal, or redefine the decision goal until the rescue work is over, and then start the rescue work.

After the earthquake, the police will be informed by the alarm notification, and the local government departments started the emergency plan according to the earthquake level, and reported the disaster information to the higher authorities. Establish a rescue command center to communicate
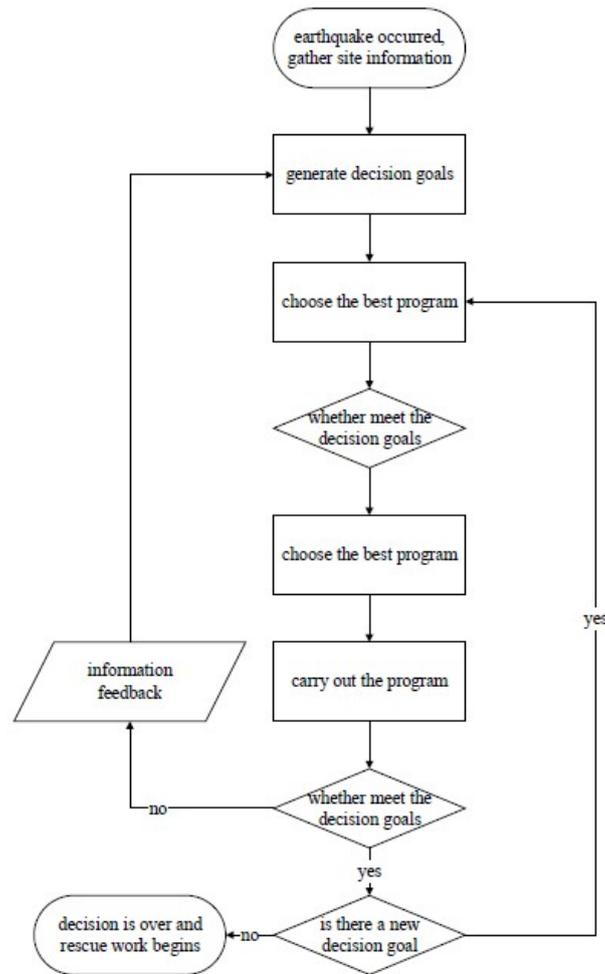
Figure 1: Earthquake emergency rescue decision process chart

instructions to emergency departments at the same level and below. The purpose of the immediate start-up of the emergency plan is to first minimize the disaster level; at the same time, a rescue expert group is established to consult on specific emergency measures, and a special department is set up under the emergency rescue command center to participate in the rescue, to clarify its responsibilities and to initiate specific rescue measures.

After receiving the notice of the emergency command center, the main rescue organizations will organize personnel to set up relevant special departments to carry out rescue activities. Although the rescue activities of various organizations will be carried out at the same time, there will be a certain priority due to the constraints of objective conditions.

3.2 Learning and Construction of Deep Belief Networks

3.2.1 Learning method of dynamic incremental expectation maximization of Bayesian network parameter

After obtaining the new sample data information, the prior probability of the node will change from $P(\theta|I_0)$ to $P(\theta|D, I_0)$, in which D is dynamically added information after data update, $D = D_1, D_2, \cdots, D_n$, and I_0 is Prior Information. When the sample data changes, the prior information involved in the calculation needs to synthesize the current input information D based on the original prior information I_0. It can be seen that the idea of this algorithm is to dynamically adjust the new information based on the original sample data.

Using dynamic incremental expectation maximization Bayesian network parameter learning method can simplify the research process and carry reasonable sample data. Before learning the parameters, two concepts should be assumed as the basis:

1. For conditional probability parameters θ, the dynamically added sample information D and prior information I_0 are independent of each other;

2. Obtain conditional probability parameters θ through calculation of the likelihood function;

However, since the learning information is derived from dynamic updates, in order to improve the efficiency of obtaining conditional probability parameters, each data update relies entirely on new data, and re-learning parameters is inefficient. We can change our thinking, consider the original sample data set separately from the new data set, and treat the new learning process as a "superposition" of conditional probability parameters. However, the above-mentioned superposition is not a simple numerical superposition. There is correlation knowledge between the historical condition probability parameter and the new parameter, which needs to be taken into consideration during the calculation process. The considerations are as follows:

1. Conditional probability parameters θ of the original data;

2. Likelihood function calculation of new data.

The above two aspects are the basis for the establishment of dynamic incremental expectation Bayesian network parameter learning methods. Here, the likelihood function of the dynamically added sample data set is represented by a function $F(\theta)$, written as:

$$F(\theta) = \eta M_D(\theta) - d\left(\theta, \bar{\theta}\right) \quad (4-1)$$

Where, $\bar{\theta}$ is old parameter value; θ is new parameter value; $\eta M_D(\theta)$ represents the data information after introducing the likelihood function of the dynamically added data D is independent, and is not affected by the posterior conditional probability parameter $\bar{\theta}$; η is learning rate, the learning rate determines the degree of correlation between the old and new parameters. The value range of η is $[0, 1]$, when it approaches 1, it means that the parameter update speed is faster, and the effect is more significant; when it approaches 0, it means that the parameter update speed is slow, and the effect becomes weak; $d(\theta, \bar{\theta})$ is estimated distance between $\bar{\theta}$ and θ. Calculating the distance estimate can reduce the parameter adjustment range and make the calculated new value closer to the historical value. This probability is a χ^2 distance. Its calculation is as follows:

$$d\left(\theta, \bar{\theta}\right) = \sum_i \sum_j P_{\bar{\theta}}\left(P_{a_i} = j\right) \chi^2\left(\theta_{ij}, \bar{\theta}_{ij}\right) \quad (4-2)$$

The above algorithm is a learning step based on the expectation maximization algorithm. In order to adapt to the dynamic update of sample data, it is required that the parameter learning results should also be dynamically updated as the data changes. Therefore, the above algorithm is adjusted as:

$$\theta_{ijk}^t = \begin{cases} \theta_{ijk}^t + \eta \left(\dfrac{P\left[X_i=k, P_{a_i}=j|D\right] - P\left[P_{a_i}=j|y_{t+1}, \theta^t\right]\theta_{ijk}^t}{\hat{P}\left(P_{a_i}=j\right)} \right), & P\left(P_{a_i}=j\right) \neq 0 \\[4mm] \theta_{ijk}^t, & P\left(P_{a_i}=j\right) = 0 \end{cases} \quad (4-3)$$

If there is no missing sample data, the function (4-3) can be simplified as:

$$\theta^t_{ijk} = \begin{cases} \eta + (1-\eta)\,\theta^t_{ijk}, & P\left(x_i = k | y_{t+1}, \theta^t\right) = 0 \, and \, P\left(P_{a_i} = j | y_{t+1}, \theta^t\right) = 1 \\ \\ (1-\eta)\,\theta^t_{ijk}, & P\left(x_i = k | y_{t+1}, \theta^t\right) = 1 \, and \, P\left(P_{a_i} = j | y_{t+1}, \theta^t\right) = 0 \quad (4-4) \\ \\ \theta^t_{ijk}, & others \end{cases}$$

In this paper, an adaptive adjustment method which uses no difference to drive learning is proposed, the basic idea is: when the parameter learning method tends to converge, slow down the learning rate η, and when the parameter learning method reaches the maximum value, the error will expand, and the learning rate η needs to be accelerated.

Assumption: If there is a node X_i in the Bayesian network topology, the prior information of the node is $P_{a_i} = j$, the learning rate of the conditional probability parameter θ_{ij} is η_{ij}. At the beginning of the error-driven η adaptive adjustment algorithm, the initial setting of the relevant data of the algorithm value:

1. Set the prior probability of the node X_i: $P\left[X_i = k | P_{a_i} = j\right] = \theta^t_{ijk}, k = 1, 2, \cdots, m$;

2. Set the initial learning rate η_{ij}. It is generally set to close to 1 in the initial situation so that the learning rate can be increased at the beginning.

3. $t = 0, \delta_t = 0$. t is the number of occurrences, δ_t indicates the number of occurrences of $P_{a_i} = j$ since the latest update η_{ij}.

According to the conditions set above, the calculation process of the adaptive adjustment algorithm is as follows:

After the sample set is updated, the dynamic incremental expectation maximization algorithm is adopted to estimate its conditional probability parameters as θ^t_{ijk}, η in function $(4-3)$ turn into η_{ij}.

If the error between the estimated value and the mean is large, increase the learning rate of the learning conditional probability parameter θ_{ij}, and $\theta^t = 0$.

In other cases, $\theta^t = \theta^t + 1$.

3.2.2   Calculation of decision property weight

At present, the methods of constructing and analyzing multi-indicator system mainly include hierarchical analysis and main component analysis. Among them, the hierarchical analysis method (AHP) decomposes the relevant elements of decision analysis into targets, standards, indicators, etc. On this basis, quantitative and qualitative analysis can be used for the thinking process of mathematical decision-making and reducing quantitative information. It is mainly applicable to situations where the factor structure is complex and the indicator needs to be quantified according to experience.

There are many factors affecting the casualties and economic losses of earthquake disasters, based on expert experience, the target layer, the standard layer and the index layer are used to construct the index system of the key influencing factors of earthquake casualty. The target layer is the key factor of earthquake casualty, and the standard layer includes earthquake, natural environment and economic and social factors. The indicator layer contains 13 indicators. Details of the indicator system are shown in Table 3.

After determining the hierarchy of the indicator system, it is necessary to quantify the effect of various factors on the casualties at the indicator level. According to the indexing process of the above analysis method and the knowledge associated with the decision factors, the judgment matrix is constructed by comparing the indicators under the same standard layer, the weight values of each indicator are calculated, and the transformation from qualitative index to quantitative index is completed.

3.3   Introduction of CBR

3.3.1   Pre-processing of properties in case

In the process of earthquake emergency rescue decision-making, a variety of decision-making factors are handled, and in the case of unprocessed, the decision factors are usually characterized by different

Table 3: Decision-making factors for earthquake emergency rescue

the target layer	decision-making factors for earthquake emergency rescue		
the standard layer	earthquake characteristics	natural environment	social environment
the index layer	magnitude intensity focal depth earthquake time	physical characteristics weather secondary disasters	population density seismic performance of buildings people indoors or outdoors building collapse rate capability and rapidity of emergency rescue material reserves

types of data, such as numerical type (continuous type, discrete type, etc.), descriptive data (Boolean type, image) and so on. When establishing a case library, the presentation of the case should be considered firstly and the data type of the decision factor needs to be unified. The general method of processing data is to divide continuous numerical values and symbolize non-numeric information. At the same time, it is necessary to unify the unit of data and the value interval. After the data is processed, the system assigns equal weights to each property in the initial stage. The basic type of earthquake emergency rescue case data information is shown in Table 4.

Table 4: Types of earthquake case data information

Type	Specific	Unit symbol
Numerical data	numerical data are generally divided into discrete and continuous data discrete data: The number of values is limited, intermittent, and discontinuous continuous data: Data that takes values within a full numeric interval, or may be indeterminate values indeterminate values	intensity: magnitude 8
Descriptive data	non-numerical data is generally descriptive and is usually described when non-numerical data records are recorded	collapse: loose, completely collapsed

The essence of discrete non-discrete data is to divide the attribute value intervals of non-discrete data into several regions, so that they are in the same region, or to convert the data within the description range into discrete amounts of the same property values, thus updating the original data to discrete values.

3.3.2 Case library building based on K-D tree

1. Define the set of case properties X , $x_i \in X$, $i = 1, 2, \cdots, m$ where is ith attribute.

2. According to the expert experience, the initial weights of the case characteristic attributes are given, and the attributes x_i in the case characteristic attributes are arranged in descending order according to the size of the initial weight. The weight of the case characteristic attributes is recalculated as the case data is updated.

3. Select the attribute x_{max} with the highest weight among the root nodes of the K-D tree.

4. Cut the attribute value range of the root node as $y_{max} = y^1_{max} \cup y^2_{max} \cdots \cup y^n_{max}$ according to the area range, and $y^i_{max} \cap y^j_{max} = \varnothing, i \neq j$. Segmentation criteria are determined by attribute type.

5. The region node obtained after the property value domain is split as the root node, adding the second most weighted property to split the new property value domain.

6. Repeat the steps of 4 and 5 to split and add properties, all of which are split, and end the process.

3.4   Case retrieval based on similarity function K-D tree

3.4.1   Similarity evaluation functions establishing

Bayesian network parameters learning to improve similarity function:

$$Similarity\,(x, y) = 1 - \sqrt{\sum_{i=1}^{m} W_i f\,(x_i, y_i)}\,(4-5)$$

Where x_i and y_i is ith attribute value of history case x_i and target case y_i; m is number of attributes in the case.

$$f\,(x_i, y_i) = \begin{cases} 0, & x_i = y_i \\[2mm] 1-p, & x_i = X\,and\,P\,(y_i = X|y_1, y_2, \cdots, y_i, y_{i+1}, \cdots, y_m) = p \\[2mm] 1-q, & y_i = Y\,and\,P\,(x_i = Y|x_1, x_2, \cdots, x_i, x_{i+1}, \cdots, x_m) = q \\[2mm] q, & others \end{cases} \quad (4-6)$$

3.4.2   The K-D Case Library retrieving

The retrieval of the K-D case library starts with the root node of the K-D tree and traverses the K-D tree structure, and the similarity of the target case to the historical case is calculated by the similarity function. If the similarity of the matching case is within the set expert value range, the retrieved case is determined to be available and stored in the output sequence. After the search for the entire K-D case library is completed, the output of the most similar historical case is used as the result of the search.

The search process is divided into four steps:

1. During the retrieval process, if there is no searchable node, exit the retrieval;

2. If the similarity of the matching case calculated from the current node is lower than the set expert value, the result is discarded and the D value of the K-D tree is recorded as val;

3. If the historical case is not fully fit in the retrieval process, the search will be continued in depth according to the nature of the K-D tree, and the case with the highest similarity obtained will be taken as the output result;

4. Exit the retrieval process.

3.5   Earthquake emergency rescue model structure based on DBN-CBR

The state of crisis after an earthquake is a sudden outbreak, but the scope and depth of its impact cannot be dealt with and ended in a short time. After receiving the earthquake information, the command center, the government function department and the transfer advisory body will make the decision-making objectives according to the emergency plan, and make the corresponding decision plan, through the evaluation, analysis and comparison of multiple sets of programs, to determine the optimal plan, so as to implement the rescue work. After the rescue, those organizations will judge the extent of the decision-making objectives according to the effectiveness of the rescue, or re-set the

decision-making objectives until the end of the rescue work, then start the construction work. In summary, the DBN-CBR-based earthquake emergency rescue model is shown in Figure 2.

The implementation of the earthquake emergency rescue decision model can be summarized into the following three steps:

1. According to the historical case of earthquake emergency rescue obtained from data mining, establish the original earthquake emergency rescue case library, unify the representation of cases, and delete unreasonable and unrelated cases of earthquake emergency rescue.

2. On the basis of the earthquake emergency rescue case database, the deep confidence network of earthquake emergency rescue properties is established, the Bayesian network parameters are studied, the relevant knowledge between the attributes is obtained, and the weight of each attribute is calculated.

3. The decision maker takes the matching case as a reference to further analyze the target case to determine that the matching result will lead to the solution that is closest to the decision objective. After the case is corrected, the modified case is stored in the case library.

4 Experimental results and analysis

4.1 Data preparation

4.2 System analysis

This paper selects the 6.5-magnitude earthquake in Ludian County, Zhaotong City, Yunnan Province, as an example, and collect the original case information as shown in Table 5.

Table 5: Original Data Table of Zhaotong earthquake in Yunnan

Classification	Decision factors	
Earthquake characteristics	magnitude intensity focal depth earthquake time	magnitude 6.5 magnitude8,9 12km 16:30
Natural environment	physical characteristics weather secondary disasters	unstable zone, very vulnerable to damage lightning strike severe landslides, floods
Social environment	population density seismic performance of buildings people indoors or outdoors building collapse rate capability and rapidity of emergency rescue material reserves	277/km2 bad 75% 97% 85% bad

Pre-processing of case data, discrete data standards as shown in Table 6.

Based on this, the raw data of Zhaotong earthquake in Yunnan are processed, and the sample data after the dispersion are obtained, as shown in Table 7.

According to the calculation of the dynamic incremental maximum expected parameter learning method in Equation 4-1, the weights of the attributes of each seismic decision factor can be obtained, as shown in Table 8.
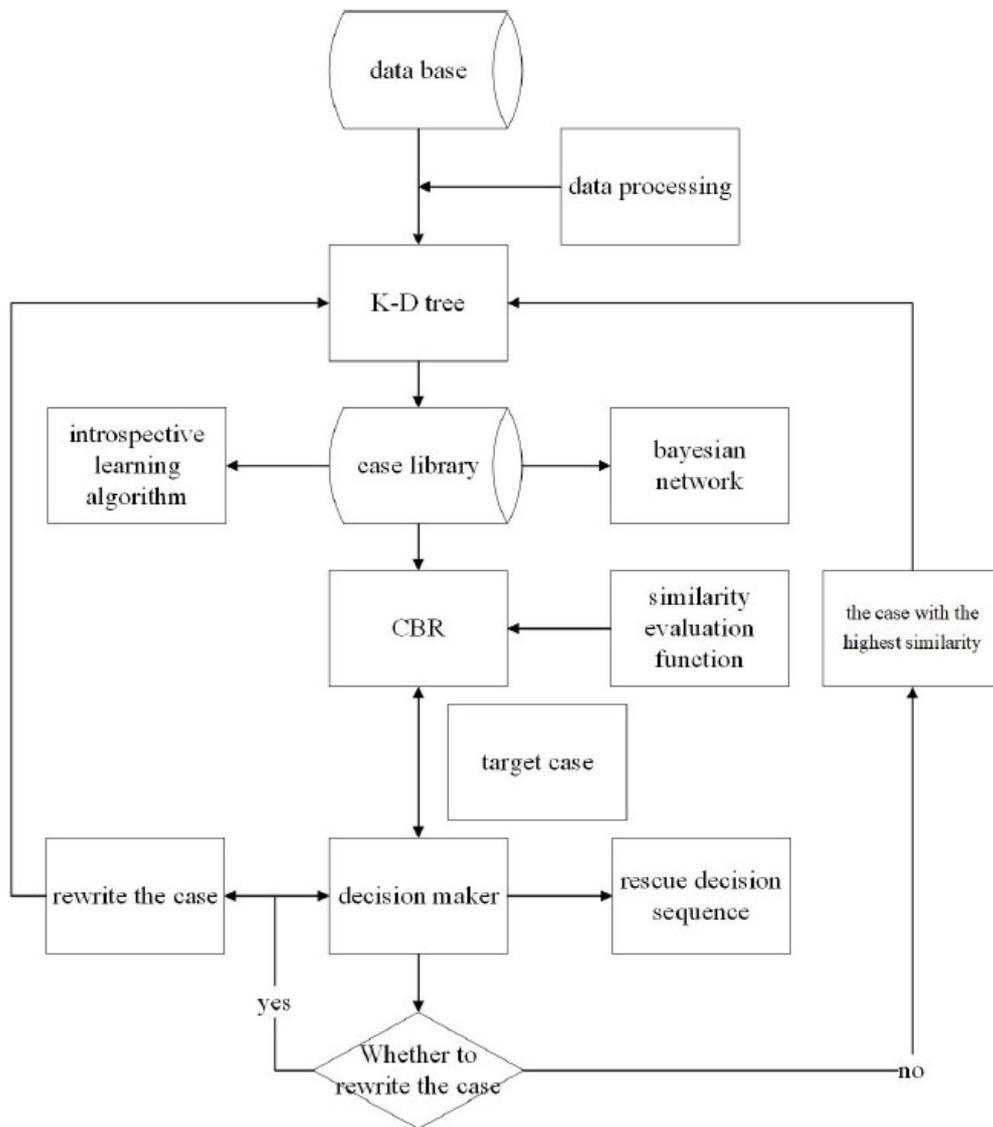
Figure 2: the DBN-CBR-based earthquake emergency rescue model

Table 6: Discrete properties corresponding to the decision factors of earthquake emergency rescue

Attribute code	Decision factors	Discretization interval
A	magnitude	1:(1-4.5) 2:(4.5-6) 3:(6-)
B	intensity	1:(1-4) 2:(5-8) 3:(9-12)
C	focal depth	1:(300-) 2:(60-300) 3:(0-60)
D	earthquake time	1:(9:00-17:00) 2:(17:00-23:00) 3:(23:00-9:00)
E	physical characteristics	1:(stable) 2:(general) 3:(fragile)
F	weather	1:(normal) 2:(general) 3:(serious)
G	secondary disasters	1:(normal) 2:(feneral) 3:(serious)
H	population density	1:(0-25) 2:(25-100) 3:(100-)
I	seismic performance of buildings	1:(good) 2:(general) 3:(bad)
J	people indoors or outdoors	1:(0-29%) 2:(30%-49%) 3:(50%-100%)
K	building collapse rate	1:(0-29%) 2:(30%-49%) 3:(50%-100%)
L	capability and rapidity of emergency rescue	1:(50-100%) 2:(30%-49%) 3:(0%-29%)
M	material reserves	1:(adequate) 2:(general) 3:(worse)

4.3   System modeling and experiment

The earthquake emergency rescue decision model system is built on the platform environment of Matlab R2018b, Visual Studio 2018 and Access 2016. The design idea is to provide the calculation support for the sample data by Matlab, where the fuzzy reasoning is used to evaluate the seismic hazard level, to determine whether a rescue plan is needed immediately, and the case reasoning results are displayed in the form established in VS.

1. Earthquake danger level simulation

Set the input variable membership function: earthquake magnitude membership function, natural environment membership function and social environment membership function, set output variable membership function, that is, earthquake danger level membership function. The fuzzy reasoning decision algorithm is designed, and the fuzzy rule browser user displays the membership function of the input and output corresponding to each fuzzy control rule. By setting the input amount, the fuzzy rules used and the corresponding output can be obtained directly by fuzzy reasoning. In the Fuzzy Inference System Editor interface, click View-Surface, which pops up the Surface Viewer interface to display a 3D graphic of the fuzzy system simulation results.

The result shows that the earthquake danger level in Zhaotong, Yunnan, is serious and the rescue plan needs to be given immediately.

2. DBN-CBR-based earthquake emergency rescue decision-making module interface

Enter the information for the target case and calculate the similarity to match the case. In the case library, the matching case with the highest similarity of 0.754 was retrieved, and this case is the Sichuan Lushan earthquake, its rescue plan was to send 7,491 rescue soldiers to the disaster area to carry out the rescue. Also, there were more than 10,000 soldiers as a reserve force in Chengdu Military Region and the Armed Police Force. After arriving in the disaster area, a total of 24 townships in Lushan County, Baoshan County and other surrounding areas were checked, more than 2,000 people had their medical treatment and health checks. And health and epidemic prevention had been carried out.

4.4   Results and analysis

From the experiment results, the seismic factor of The Zhaotong earthquake in Yunnan was 0.955, the natural environment factor was 0.537, the social environmental factor was 1.04, the danger level of 2.04 was obtained by fuzzy reasoning, and the danger level of Zhaotong earthquake in Yunnan was

Table 7: Discrete properties corresponding to the decision-making factors of Zhaotong earthquake emergency rescue in Yunnan

Attribute code	Decision factors	Discrete attribute
A	magnitude	3
B	intensity	2
C	focal depth	3
D	earthquake time	1
E	physical characteristics	3
F	weather	2
G	secondary disasters	3
H	population density	3
I	seismic performance buildings	3
J	people indoors or outdoors	3
K	building collapse rate	3
L	capability and rapidity of emergency rescue	1
M	material reserves	3

Table 8: Weight of Factors in Earthquake Emergency Rescue Decision

Attribute code	Decision factors	Weight
Earthquake characteristics	magnitude	0.1286
	intensity	0.1117
	focal depth	0.0814
	earthquake time	0.1014
Natural environment	physical characteristics	0.0640
	weather	0.0463
	secondary disasters	0.0841
Social environment	population density	0.1160
	seismic performance buildings	0.1035
	people indoors or outdoors	0.0650
	building collapse rate	0.0273
	capability and rapidity of emergency rescue	0.0557
	material reserves	0.0150
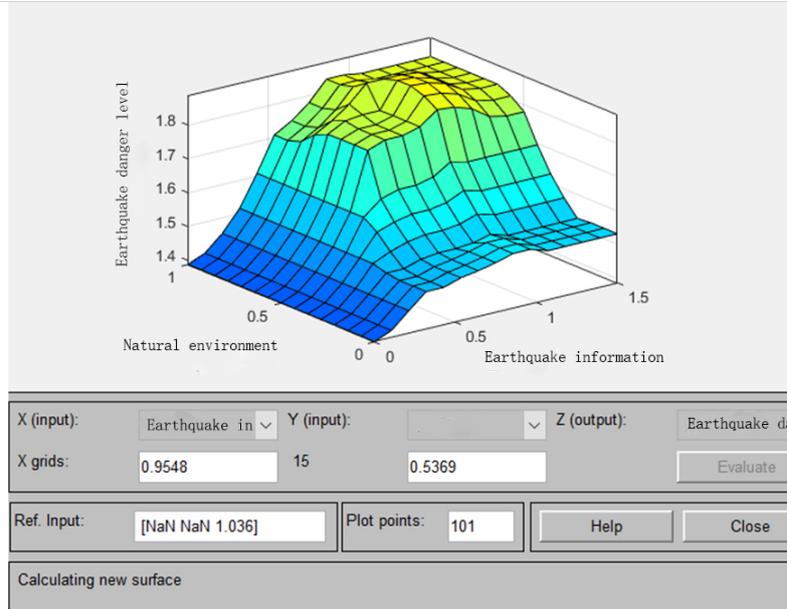
Figure 3: 3D map of earthquake danger level simulation results

No.	Similarity	Solution
1	0.754	sent 7491 soldiers to the disaster area for rescue

Figure 4: Earthquake emergency rescue decision case match results based on DBN-CBR

severe according to the fuzzy rules, and the solution needed to be given immediately. Then this paper sets the decision goal and starts the case search.

During the case matching, the Lushan earthquake magnitude 7.0, intensity of 9, the depth of the earthquake is 13km, while the Zhaotong earthquake magnitude 6.5, intensity of 8 and 9, the depth of the earthquake is 12km; There are a wide range of secondary mountain disasters, manifested in mudslides and landslides. As for social environment, the level of economic development is low, there are several state-level poor counties. And seismic performance of houses is weak, collapse rate of buildings after the earthquake is very high, and there were heavy casualties in these two earthquakes. And when we determine the earthquake danger level, the earthquake danger level of these two places is the same as serious. It is immediately to have a rescue plan. The seismic characterization of the two places is very similar. The result of the final case match is that the Lushan earthquake has the highest similarity with the Zhaotong earthquake in Yunnan, so the emergency rescue plan of the Lushan earthquake can be used as the decision-making support of the Zhaotong earthquake in Yunnan.

In fact, after the Zhaotong Ludian earthquake, nearly 10,000 officers and soldiers from Chengdu, Beijing, the Air Force's Second Artillery and Armed Police Military Regions all arrived in 13 disaster-stricken counties and 13 heavily affected townships. It is similar with the Sichuan Lushan earthquake. The actual rescue plan of the two earthquakes both focuses on sending a large number of troops to check the personnel and prevent secondary geological disasters. The actual situation and the experimental results of this paper are highly consistent.

5   Conclusions

Taking earthquakes as an example, this paper combines DBN and CBR algorithms to apply to emergency rescue decision-making, improves case representation and case retrieval steps in the case reasoning process, and then, on the basis of the existing seismic emergency rescue theory system, designs a decision-making model for an earthquake emergency rescue by using the logical structure of case reasoning. Finally, the proposed model is verified by a real case. Therefore, the model proposed in this paper has practical significance in emergency rescue decision-making. It can improve the deficiency of the existing decision-making reasoning method, enrich existing emergency decision-making theory, and can help decision makers make more targeted decisions. On this basis, this paper makes the following suggestions:

1. When making emergency decisions, in addition to drawing on the advice of experts, scientific decision-making methods are necessary;

2. Continuously improve the existing case library to improve the selectivity of case matching;

3. Optimize decision-making methods from various angles to improve the accuracy of case matching.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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