The Emergency Response Management Based on Bayesian Decision Network

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***Abstract*—In order to solve the emergency decision management problem with uncertainty, an Emergency Bayesian decision network (EBDN) model is used in this paper. By computing the probability of each node, the EBDN can solve the uncertainty of different response measures. Using Gray system theory to determine the weight of all kinds of emergency losses. And then use genetic algorithm to search the best combination measure by comparing the value of output loss. For illustration, a typhoon example is utilized to show the feasibility of EBDN model. Empirical results show that the EBDN model can combine expert's knowledge and historic data to predict expected effects under different combinations of response measures, and then choose the best one. The proposed EBDN model can combine the decision process into a diagrammatic form, and thus the uncertainty of emergency events in solving emergency dynamic decision making is solved.**

Keywords—Bayesian decision network; expert knowledge; emergency decision; emergency

I. Introduction

The emergence events have been major threats to social stability and life safety. So, it is necessary to strengthen the public safety management, while the core task of which is emergency management [1]. However, given the uncertainty of the emergency events, different contingency plans may lead to different consequences of the emergencies. In the face of numerous factors and emergency measures, the scientific decision becomes very difficult. How to choose the best combination among the multiple alternative emergency measures becomes vital important in terms of the mitigation effects.

In the recent decades, various methods for emergency decision have been developed, which are generally divided into three groups: (1) Methods based on multi-attribute utility analysis. Evaluate the impact of each factor in the decision-making process, then select the solution with the highest utility [1] [2] (2) Methods based on fuzzy comprehensive assessment. Define membership functions to obtain the membership grade of each decision scheme, and then choose the best decision by comparing membership grade [4][5] . However, applied in an emergency event, the two methods above have limitations: the decision making is based on comparing the utility of each contingency plan, but the uncertainty of the process of emergency event is neglected. (3) Methods based on Bayesian network. Make decisions upon each option's expected value after analyzing the probability distribution of the options based on the Bayesian theory[6][7]. Although this method considering the probability distributions in different situations, it still has some limits: emergency event is a system which has high uncertainty. This method can't choose the control methods dynamically in the process of emergency events.

A Bayesian Decision Network (BDN) is defined as a Bayesian network that has been modified to include decision (management option) variables and utility (benefit-cost) variables. These modifications make a BDN useful for evaluating multiple combinations of management options and examining the resulting costs or benefits. For its rich ability to integrate knowledge in different fields and to deal with uncertainty, BDN has become useful tool to describe and solve the complex decision-making problems. The implementation of BDN has been growing in the last years. For example, Bayesian decision networks have been implemented to integrate assessment of sea-level rise adaptation strategies based on expert system [8]. Sadoddin developed a Bayesian decision network approach to assess the ecological impacts of salinity management using expert' s knowledge and historic data [9]. Jenifer L constructed a Bayesian Decision network, which can update the probability timely to assess the sustainability of the coastal lakes [10]. Although BDN is growing, it is still rather scare in emergency decision making. Since BDN can consider and integrate knowledge in different fields and is rich in expressing probability and dealing with uncertainty, this article constructs an Emergency Control Bayesian Decision Network (ECBDN) with the purpose to obtain the most effective control measures. The approach proposed here focuses on the management of uncertainty and expert knowledge in the decision process. Firstly, analyze the components and structure of the emergency system using the knowledge of system theory. And then combine with Bayesian decision network principle to build an Emergency Bayesian Decision Network (EBDN) model. Next, using the Grey System Theory to determine the weight of all kinds of emergency losses, and calculate the value of the output loss under different control measures. Finally, use typhoon as example to demonstrate its effectiveness in practice.

The paper is organized as follows: In Section II, the Emergency Bayesian Decision Network was illustrated. In Section III, we present an innovative approach for optimizing the emergency response measures using Grey System Theory. Case study about the typhoon is used to demonstrate the validity of this method proposed in Section IV. Section V draws some important conclusions on the results and comments on the potentials of the proposed approach.

II. METHOD

In this section, considering emergency as a system, a framework for structure learning of BDN is illustrated. The method can help us easily know the relationship among variables.

A. *The Selection of Variables*

The emergency events can be divided into four parts, they are input elements, state elements, output elements and value elements. These four elements are described by variables, which constitute the nodes of the Bayesian decision network. The four variables are as follows:

1) Input variables. The input variables are composed of environmental input (EI) and control input (CI). EI will affect the crisis events' state. CI are taken by the related organizations in order to prevent the evolution of crisis events and to reduce the losses.

2) State variables. State variables include the states of events (ES), events phase variables (P), and the states of hazard affected body (BS).The hazard-affected body means a series of entities that can be affected by crisis events, such as population, buildings.

3) Output variables (O). The output variables refer to the output factors of an emergency event system, which influences the external environment, such as damages, some abnormal substances, and other factors. In this paper, output variables are denoted by chance nodes, which describes the losses caused by emergency events.

4) Value variables (U). Value variables are signified by value nodes, which are descriptions of the output values for event losses in emergency system.

B. *Construction of Emergency Bayesian Decision Network (EBDN)*

There are three methods to build the model of the Bayesian Decision Network:

- Build the Bayesian decision network by hand based on experts' knowledge.
- Directly generate the BDN model automatically using the machine learning method.
- Construct the BDN model by combining the first and the second method. Firstly, collect historical data; then construct a network structure through the sample data learning; at last, modify the decision network structure depended on the opinion of experts in the field. This paper used the third method to construct the BDN model.

Let $EI = \{ei_r | 1 \le r \le m\}$ denotes the set of environmental input in the emergency system. $CI = \{\mathrm{ci_r} | 1 \le r \le n\}$ is the set of control input. $ES = \{\mathrm{es_r} | 1 \le r \le \mathrm{p}\}$ is the events' state variables set; P is the events' phase variables set , $BS = \{\mathrm{bs_r} | 1 \le r \le q\}$ describes the state of hazard-affected bodies that are influenced by the crisis events. $O = \{\mathrm{o_r} | 1 \le r \le j\}$ is output variables set; $U = \{\mathrm{u_r} | 1 \le r \le j\}$ is value variables set. The structure of EBDN can be built according to the relationships among these variables as shown in Fig. 1.

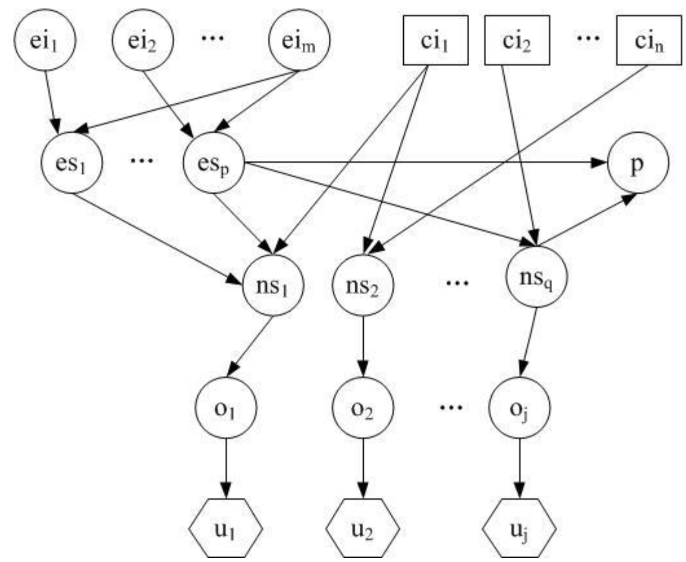

Fig. 1 Structure of the EBDN

We use a three-triple $G = < N, E, P >$ to denote the EBDN, where $N = EI \cup CI \cup ES \cup BS \cup P \cup O$ denotes the set of nodes, and each node represents an element of emergency event. E is the set of direct edges, and every edge indicates a dependency relationship between the two nodes. Each parameter in P shows the conditional probability of each node variable in the network. According to Bayes theorem, the joint probability of all of the nodes can be calculated as (1):

$$\begin{aligned}&\mathrm{P}(ei_m, ci_n, ms_p, ns_q, p, o_j) = \\ &P(ei_m) * P(es_\mathrm{p} | ei_m) * P(\mathrm{es_p} | \mathrm{ci_n}) * P(bs_q | ci_n) * P(bs_q | es_p) \\ &* P(p | es_p, bs_q) * P(o_j | es_p) * P(o_j | bs_q)\end{aligned} \quad (1)$$

P（$\mathrm{ei_m}$）is the probability of EI, $P(\mathrm{es_p} | ei_m)$ represents the conditional probability between EI and ES. $P(\mathrm{bs_q} | ci_n)$ represents the conditional probability between CI and BS. $P(\mathrm{bs_q} | es_p)$ represents the conditional probability between ES and BS. $P(\mathrm{p} | \mathrm{es}_p, bs_p)$ represents the conditional probability among ES, BS and P. $P(\mathrm{o_j} | \mathrm{es}_p)$ represents the conditional probability between ES and O. $P(\mathrm{o_j} | \mathrm{bs}_q)$ represents the conditional probability between BS and O.

III. OPTIMIZATION OF EMERGENCY RESPONSE MEASURES

A. *Calculation of the Weight Set of Emergencies Loss*

The main current methods in disaster loss assessment are fuzzy comprehensive assessment and gray fuzzy comprehensive assessment [11]. Some factors which caused disaster losses are difficult to use an accurate value to represent. And the disaster losses possess both fuzzy system and gray system' s character. So the gray -fuzzy appraisal method is proposed. This method can solve the difficulties of factors' choosing and the weights' determining, which makes assessment more objective and scientific. The gray - fuzzy appraisal method proposed by Wu [11] is used in this paper. Firstly, determine the weight set of output losses using gray relational analysis based on the historic data. The major steps as follows:

1) Determine the factor set of disaster losses based on the emergency instances. There will be a domain $S=[s_1,s_2,\ldots,s_n]$ when n emergency events are chose. s_i denotes the i instance which can be denoted as $s_i=[x_{i1},x_{i2},\ldots,x_{im}]^T$. Let x_{ij} denote the j output losses of the i instance. If each instance has m outputs, we can obtained the $m\times n$ matrix L, which illustrates the sample of the emergency events. L is denoted as follows:

$$L=\begin{bmatrix} x_{11} & \cdots & x_{n1} \\ \vdots & \ddots & \vdots \\ x_{1m} & \cdots & x_{nm} \end{bmatrix}$$

2) Normalization. In order to analyze conveniently, we do normalization using (2):

$$y_i(j)=\frac{x_{ij}}{\frac{1}{k}\sum_{i=1}^{n}x_{ij}} \tag{2}$$

3) Relevance analysis. First, determine the generating sequence. Let $y_0=[y_o(1),y_0(2),\ldots,\ y_0(n)]$ denote it, where $y_0(n)$ is the loss parameter of emergency events. The relevance set is denoted by $R=[r_1,r_2,\cdots,r_m]$. Variable r_i can be calculated as (3).

$$r_i=\frac{\sum_{n=1}^{m}\xi_i(n)}{m} \tag{3}$$

where $\xi_i(n)$ is defined as follows:

$$\xi_i(n)=\frac{\min\limits_i\min\limits_n|y_0(n)-y_i(n)|+\rho\max\limits_i\max\limits_n|y_o(n)-y_i(n)|}{|y_0(n)-y_i(n)|+\rho\max\limits_i\max\limits_n|y_o(n)-y_i(n)|}$$

where ρ =0.1~1.0.

4) Determine the weight set. The weight set $A=[a_1,a_2,\ldots,a_m]$ can be got after the relevance set R obtained, where a_i can be calculated as (4):

$$a_i=\frac{r_i}{\sum_{j=1}^{m}r_i},\ i=1,2,\ldots,\ \ m \tag{4}$$

B. *Optimization of the Emergency Response Measures Based on Genetic Algorithm*

Genetic Algorithms is chosen by this paper because of its powerful global searching ability [12]. The design of genetic algorithm is as follows:

1) Coding design. Let $CI=\{ci_1,ci_2,\cdots,ci_m\}$ represent M response measures, where $m=1,2,\cdots,M$. Each response measure is denoted by x_m which is regarded as individual gene. Chromosome coding is described by $(x_1,x_2,\cdots,x_m)$, where $x_m\in[1,N]$ because each response measure has N states.

2) Population design. The initial population is generated by random number generator.

3) Fitness function design. Regard each group combination (that is each chromosome) as evidence, reason on EBDN. If there are j losses, the output losses can be denoted by $O=\{o_1,o_2,\cdots,o_n\}$, where $n=1,2,\cdots,j$. Let $P(CI=X)$ represent the prior probability that the control measure CI in the state of X. Each output losses o_n has Q states $(o_n\in1,2,\cdots,Q)$. The conditional probability of each state can be calculated as (5):

$$P(o_n=q|ci_1=x_1,ci_2=x_2,\cdots,ci_m=x_m) \tag{5}$$

where $q=1,2,\ldots,Q$. Then the expected economic value of each loss can be calculated as (6):

$$e_n=\sum_{q=1}^{Q}u(o_n=q)P(o_n=q|ci_1=x_1,ci_2=x_2,\cdots,ci_m=x_m) \tag{6}$$

where u is an economical value, which can be obtained by the historical data.

The fitness function can be denoted as (7) based on the weight a_n which is calculated by (4)

$$\mathrm{fit}(x)=\sum_{n=1}^{j}e_n a_n \tag{7}$$

IV. EXPERIMENTAL EVALUATION

A. *The EDBN of Typhoon*

Typhoon is a common emergency natural disaster. It can cause heavy losses to coastal areas, for it may lead to floods and landslides. This paper chose a typhoon event to illustrate the process of emergency response decision options.

First, the related variables of the typhoon event are extracted from the statistical files, and these variables are composed of input variables, state variables and output variables. The variables for the EBDN are shown in TABLE I.

TABLE I. VARIABLES FOR THE BAYESIAN DECISION NETWORKS OF TYPHOON

Variables	Variable name	States	Variable meaning
Input variables	Tropical Cyclones	exit; not exit	The tropical cyclones which caused typhoon exit or not.
	Sea Temperature	<26℃; >=26℃	Sea surface temperature of the tropical cyclone formation
	Emergency Transfer	<=1million; 1million~10million; >10million	Emergency transfer measures when typhoon occurred
	Protective Barrier	Yes; no	Install barrier at the landslide
	Building Reinforcement	yes; no	Reinforce the building of The typhoon- prone areas
State variables	Barometric Pressure	<980 hPa >=980 hPa	The tropical cyclone center pressure.
	Typhoon Intensity	<=32m/s; 32~42m/s; >42m/s	The tropical cyclone maximum wind speed
	Radius	<=100km; 100~200km; >200km	The radius of the cyclone
	Population	<5 million; 5million~15million; >=15million	Density of population in disaster areas
	Houses	<100 thousands; 100 thousands～300thousands; >=300 thousands	The number of houses in disaster areas
	Crops	<1 million; 1million~3million; >=3 million	The affected areas of crops in disaster areas
Output variables	Casualties	0～10; 10～100; >=100	The number of injuries and deaths
	Agricultural losses	<100millions; 100millions~1billion; >=1billion	Economic losses of crop failures
	Houses Damage	<=5000; 5000~15000; >15000	The number of houses damaged or collapsed

Then, based on the data of typhoon events in 2000~2006, the structure of a Bayesian network is constructed by K2 algorithm. Then, the structure is modified according to the knowledge of the experts in this area. The control nodes of Emergency Transfer, Protective Barrier and Building Reinforcement are changed into decision nodes, and each output node is connected to the right utility node. Finally, the Netica software is used to formulate the final Bayesian decision network, as Fig. 2 This EBDN can integrate different domain knowledge, and the causality of each node can be represented in the graphical network.

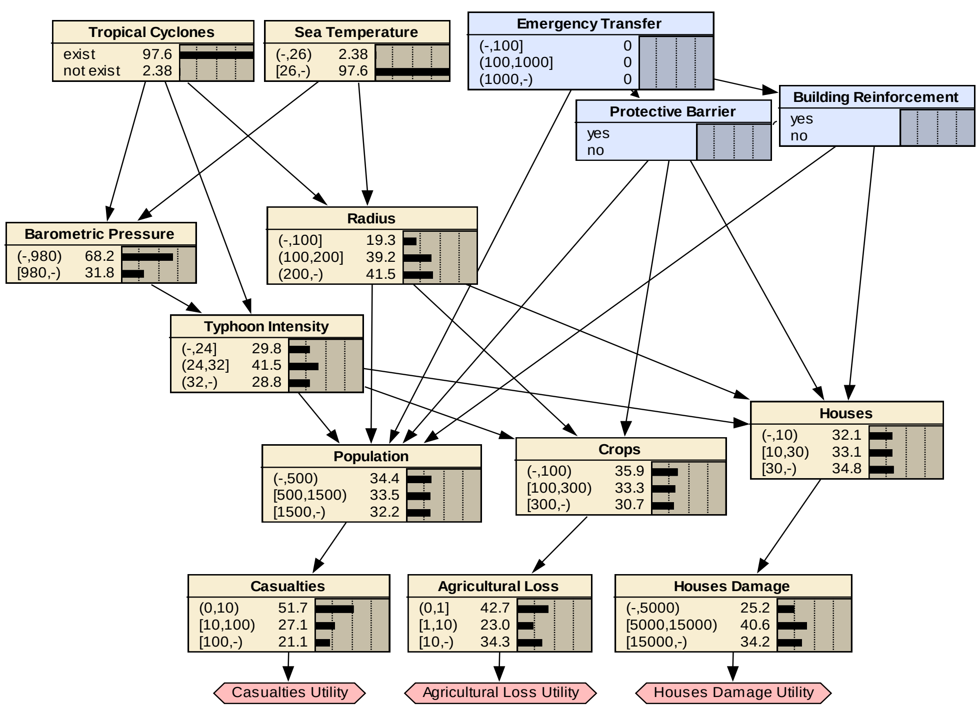

Fig. 2 The Bayesian decision network of typhoon events

In Netica software, the joint probability distribution of all the variables and the conditional probability tables for each node can be obtained by parameter learning, as shown in Table II.

TABLE II. THE CONDITIONAL TABLE OF TYPHOON EBDN

Variable name	States	Prior Probability
Tropical Cyclones	Exit; not exit	(0.984,0.0161)
Sea Temperature	<26℃;>=26℃	(0.0161,0.984)
Barometric Pressure	<980 hPa; >=980 hPa	(0.641,0.359)
Typhoon Intensity	<=32m/s;32~42m/s;>42m/s	(0.314,0.455,0.231)
Radius	<=100km;100~200km;>200km	(0.21,0.38,0.41)
Population	<5million;5million~15million; >=15million	(0.348,0.341,0.312)
Houses	<100 thousands; 100 thousands～300thousands; >=300 thousands	(0.322,0.362,0.316)
Crops	<1 million;1million~3million; >=3 million	(0.338,0.377,0.285)
Casualties	0～10、10～100、>=100	(0.518,0.279,0.203)
Agricultural losses	<100millions;100millions~1billion;>=1billion	(0.398,0.288,0.315)
Houses Damage	<=5000、5000~15000、>15000	(0.275,0.396,0.329)

There are three kinds of responses about typhoon events, the different states of the control measures combined with each other to obtain 3 * 2 * 2 = 12 kinds of combination of control measures, as shown in Table III. The experimental data are acquired from the files of No.23 Typhoon "Fitow" (landing pressure 955 hPa, typhoons radius is 350m, the maximum wind speed is 45m / s) in 2013, which is taken as an evidence to manifest the effectiveness of the proposed approach.

TABLE III. THE COMBINATION OF MEASURES IN TYPHOON EVENTS

Combination	Emergency Transfer	Protective Barrier	Building Reinforcement
C1	<=1million	Yes	Yes
C2	<=1million	Yes	No
C3	<=1million	No	Yes
C4	<=1million	No	No
C5	1million~10million	Yes	Yes
C6	1million~10million	Yes	No
C7	1million~10million	No	Yes
C8	1million~10million	No	No
C9	>10million	Yes	Yes
C10	>10million	Yes	No
C11	>10million	No	Yes
C12	>10million	No	No

According to the proposed method in section III, the weight set $A=[0.485,0.226,0.289]$ can be calculated. Followed by building damages and agricultural losses, it can be claimed that casualties cause the largest losses.

At last,design the Genetic Algorithm.

Set ET to represent Emergency Transfer, PB to represent Protective Barrier, BR to represent Building Reinforcement. Chromosome encoding as (x_1, x_2, x_3) , $x_1 \in \{1,2,3\}$, $x_2 \in \{1,2\}, x_3 \in \{1,2,3\}$, the output is $\{o_1, o_2, o_3\}, o_i \in \{1,2,3\}$.

Economical values of each output are shown in Table IV.

TABLE IV. THE ECONOMICAL VALUES OF EACH OUTPUT

	State	Economical Value
Casualties	0 ~ 10; 10 ~ 100; 100 ~	0.42; 3.57; 149
Agricultural losses	0 ~ 1; 1 ~ 10; 10 ~	0.75; 7.48; 82
Houses Damage	0 ~ 5000; 5000 ~ 15000;15000 ~	0.72; 6.34; 23

Then the fitness function is

F=

$$\begin{aligned}
&0.204\,P(o1=1|\,ET=x_1,PB=x_2,BR=x_3)+1.732\,P(o1=2|\,ET=x_1,PB=x_2,BR=x_3)\\
&+72.265\,P(o1=3|ET=x_1,PB=x_2,BR=x_3)+0.169\,P(o2=1|ET=x_1,PB=x_2,BR=x_3)\\
&+1.691\,P(o2=2|ET=x_1,PB=x_2,BR=x_3)+18.53\,P(o2=3|ET=x_1,PB=x_2,BR=x_3)\\
&+0.208\,P(o3=1|ET=x_1,PB=x_2,BR=x_3)+1.832\,P(o3=2|ET=x_1,PB=x_2,BR=x_3)\\
&+6.647\,P(o3=3|ET=x_1,PB=x_2,BR=x_3)
\end{aligned}$$

We use the optimal toolbox of MATLAB to run the genetic algorithm. The population size is 20, and other parameter according to the default settings. In this example, the results are (x1, x2, x3) = (2, 1, 1) (which means x1 is in its second state; x2 is in its first state; x3 is in its first state). In the table V, it is clearly to know that the combination 5 (transfer staff from 1 million to 10 million, fence installation, reinforced housing) is the optimal combination of the minimal utilities.

TABLE V. THE UTILITY OF EACH COMBINATION

	Casualties	Agricultural Loss	Houses Damage	The total loss
Weight	0.485	0.226	0.289	1
C1	32.80411	20.92862	8.47678	23.089651
C2	32.24759	20.92862	12.02874	23.846255
C3	35.5195	37.72767	9.25818	28.429025
C4	46.86828	37.72767	12.83564	34.967069
C5	26.69343	20.92862	8.47678	**20.125971**
C6	32.19089	20.92862	12.02874	23.818756
C7	27.93247	37.72767	9.25818	24.749315
C8	31.49209	37.72767	12.83564	27.509617
C9	26.87719	20.92862	8.47678	20.215095
C10	27.49671	20.92862	12.02874	21.542078
C11	30.62896	37.72767	9.25818	26.057113
C12	29.03921	37.72767	12.83564	26.31997

B. *Model analysis*

The variables have different effects on output losses, so the sensitivity analysis about casualties can be calculated, as the results showed in Table VI, building damages and agricultural losses are most sensitive to different combination of measures. It shows that Population and Emergency Transfer have the largest effect on Casualties. Protective Barrier has the largest effect on Agricultural losses; Building Reinforcement has the largest effect on Houses Damage. Therefore, synthesizing the weight and sensitivity, Emergency Transfer should be considered firstly in the process of decision.

TABLE VI. THE RESULT OF SENSITIVITY ANALYSIS

	Casualties		Agricultural Loss		Houses damage	
	Mutual	**Variance of beliefs**	**Mutual**	**Variance of beliefs**	**Mutual**	**Variance of beliefs**
Population	0.52516	0.0924080	0.00046	0.0000722	0.00032	0.0000436
Emergency Transfer	0.00300	0.0005794				
Protective Barrier	0.00095	0.0002052	0.03400	0.0059361	0.00170	0.0002081
Radius	0.00059	0.0001326	0.00786	0.0011532	0.00469	0.0005896
Building Reinforcement	0.00053	0.0000912			0.01873	0.0024602
Crops	0.00035	0.0000754	0.60330	0.1601656	0.00094	0.0001123
Houses	0.00032	0.0000636	0.00125	0.0001998	0.51806	0.1241758
Typhoon Intensity	0.00025	0.0000494	0.00580	0.0009619	0.00301	0.0004032
Agricultural Loss	0.00021	0.0000452			0.00055	0.0000668
Houses Damage	0.00015	0.0000299	0.00055	0.0000893		
Barometric Pressure	0.00004	0.0000098	0.00269	0.0004511	0.00113	0.0001599

We compared the optimal measure with the actual measure in Table VII. According to Department of Civil Affairs of Fujian and Zhejiang Province's reports [14], 33.8 thousand people were transferred in Fujian province under the influence of Typhoon "Fitow". 78.6 thousands people were transferred in Zhejiang province. The total number of these two provinces population are 1124 thousand. In order to reduce the losses induced by the landslide, rainstorm and high tide, both of provinces launched a level-II meteorological disaster emergency response. Both of them reinforced houses and installed the guardrail on the hill. These measures are consistent with the paper's ideas. "Fitow" is the most powerful typhoon since 1949 in China, but it causes fewer casualties and social influences than the typhoon events in the past owing to the efficient precaution. Thus, the measure proposed in the paper is effective and reasonable, which can provide the theoretical basis and reduce the damage by the emergency.

TABLE VII. THE COMPARISON OF THE RESULT AND THE ACTUAL RESPONSE

Variable name	The result of EBDN	Actual response
Emergency Transfer	1million~10million	1.124million
Protective Barrier	Yes	Yes
Building Reinforcement	Yes	Yes

Bayesian decision network model is built by the Netica software can gain conditional probability table for each node automatically. The relationships between any two nodes are calculated by the K2 algorithm combining the expert's knowledge, the approach has been described in section II. The topological relation of different variables which relies on external environment is uncertainty. When the transcendental and expert's knowledge is changed, the model established in this paper could update the probability in time to gain the expected utility of nodes. The ERBDN can shorten the decision-making time and improve the decision-making efficiency.

V. CONCLUSION

This study makes a twofold contributions: (1) We regard emergency as a system based on the system theory. And then put forward a method of emergency decision making by combining the Grey System Theory and Genetic Algorithm. (2) Aiming at the uncertainty in the process of emergency, the Emergency Bayesian Decision Network (EBDN) model is constructed. This model can be used in the event containing large data and historical experience. The EBDN model proposed here can show the relationships between each node by the graph. It diminishes the uncertainty and limitation of dates. What's more, it can update the probability of each node in time. It also can search the best measures dynamically by comparing the measure's different expected utility of different measures.

The case study of Typhoon shows that the method can predict the losing output condition in different measures, and it also can evaluate the measures' availability. However, it should note that this method is suitable for the condition that has some historical data to gain the conditional probability table. When the Bayesian decision network is constructed, the topological network structure obtained by machine learning should combine with experts' revision to reduce the network's complexity and enhance the calculation veracity. Besides, an emergency is an enormous system, which may cause a series of derivative events which has tight and complicated connections. In the future, we will take connections and interaction effects between different measures into account to find the optimizing method of cascading crisis.

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THE ORIGINAL DATA OF TYPHOON

Tropical Cyclones	Sea Temperature	Barometric Pressure	Typhoon Intensity	Radius	Population	Houses	Crops	Casualties	Agricultural losses	Houses Damage	Emergency Transfer	Protective Barrier	Building Reinforcement
1	30	965	35	150	987	8	121	1	0.54	4232	2	YES	YES
1	30	930	53	300	2212	48	434	125	59.9	15989	1	NO	NO
1	30	965	33	250	567	9	61	0	0	5432	2	YES	YES
1	30	990	23	180	445	5	45	0	0	3444	3	YES	YES
1	30	970	33	180	467	8	65	0	0	4121	3	YES	YES
1	30	960	38	250	2978	23	356	154	35.88	12332	1	NO	NO
1	30	990.2	23	150	453	12	54	0	0	9843	3	YES	YES
1	30	996.5	35	200	1489	32	141	14	1.3	14434	1	YES	NO
1	30	881.1	38	350	542	43	178	1	1	15576	3	YES	NO
1	30	996.8	20	80	687	23	189	5	0.7	12312	1	NO	YES
1	30	985.9	38	250	1734	34	543	111	77	15231	1	NO	NO
1	30	890.8	40	150	1344	53	324	94	28	16242	1	NO	NO
1	30	883	35	180	341	5	159	0	4.4	3456	2	YES	YES
1	30	757.5	35	250	417	34	33	0	0	15121	3	YES	NO
1	29.5	987	18	80	989	13	97	13	0.18	9898	1	YES	YES
1	30	950	40	300	482	34	101	5	0.14	15333	3	YES	NO
1	28.5	925	51	300	561	18	103	2	0	11346	3	YES	YES
1	30	990	23	100	489	7	65	0	0	4324	2	YES	YES
1	30	990	23	100	387	8	121	0	0.7388	5653	1	YES	YES
1	30	998	18	100	645	23	212	11	14.6	15322	1	NO	NO
1	30	950	43	100	434	9	345	6	13.5	6342	2	NO	YES
1	30	975	30	180	567	9	97	4	0.184	4865	2	YES	YES
1	29.5	970	33	150	386	12	73	0	0	4667	2	YES	YES
1	30	942	45	250	1253	12	445	49	89	7868	1	NO	YES
1	30	955	40	250	243	8	67	0	0	6432	3	YES	YES

1	30	960	38	200	3341	54	312	428	18	17423	1	NO	NO
1	30	998	18	100	1439	23	287	11	17.87	13543	1	NO	NO
1	30	945	43	250	2234	65	234	110	3.5	17653	1	NO	NO
1	30	940	38	250	434	12	178	6	6.7	9894	2	YES	YES
1	30	912	55	280	1543	89	345	46	38.3148	18688	1	NO	NO
1	30	955	40	250	534	8	87	2	0.9	4355	2	YES	YES
1	30	985	25	200	234	9	56	0	0	5452	3	YES	YES
1	30	920	53	250	1924	34	234	65	16	14766	1	NO	NO
1	30	950	43	200	387	12	78	0	0	10212	3	YES	YES
1	30	925	51	200	1987	31	234	55	2.6	16345	1	NO	NO
1	30	943	45	300	478	78	99	0	1.5	20129	2	YES	NO
1	30	978	25	300	879	23	78	5	1.8	13435	2	YES	NO
1	30	960	38	200	345	9	123	4	1.6	4523	3	YES	YES
1	30	935	48	180	332	24	99	0	0	15341	3	YES	NO
1	30	985	23	120	479	9	56	0	0	3564	1	YES	YES
1	30	965	35	150	543	9	142	0	1.6	3123	2	NO	YES
1	30	930	53	300	1432	11	321	32	12	6123	2	NO	YES
1	30	965	33	250	2122	11	311	121	11	5634	1	NO	YES
1	30	990	23	180	1512	22	124	23	1.3	12312	1	YES	NO
1	30	970	33	180	1423	8	96	24	0.2	3111	2	NO	YES
1	30	960	38	250	2341	35	328	114	14	17456	1	NO	NO
1	30	990.2	23	150	342	14	145	1	1.4	11243	2	NO	NO
1	30	996.5	35	200	432	13	213	0	2.5	10972	3	NO	NO
1	30	881.1	38	350	563	15	164	0	1.9	12094	2	NO	YES
1	30	996.8	20	80	123	5	122	0	0.4	2134	3	NO	YES
1	30	985.9	38	250	432	31	312	2	15	16987	3	NO	NO
1	30	890.8	40	150	654	24	254	0	3.5	15632	2	NO	NO
1	30	883	35	180	234	21	54	0	0.6	13214	3	YES	NO
1	30	757.5	35	250	567	12	214	0	2.4	4321	3	NO	YES
1	29.5	987	18	80	342	13	99	0	0	5234	2	NO	NO
1	30	950	40	300	1142	36	312	89	21	19308	3	NO	NO
1	28.5	925	51	300	1321	24	231	65	3.1	15632	3	NO	YES
1	30	990	23	100	123	6	211	1	1.4	3467	3	NO	YES
1	30	990	23	100	123	15	123	2	0.2	13215	2	NO	NO
1	30	998	18	100	123	4	143	0	1.1	2657	2	NO	YES