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A Risk Early-warning Method in Earthquake Emergency Response based on Integrated Information Entropy and Matter-Element Model

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Abstract—**Risk early-warning is a very important task in earthquake emergency response. It is a complex prediction problem, often with inconsistent and even conflicting factors. With the integration of the matter-element theory and entropy method, we propose a new approach that integrates the early-warning objects, risk attributes and their value range into a matter-element system, to research risk early-warning system's extension nature. Through the application of extension theory, the weight coefficients of early-warning attributes are determined by using an entropy weight method. The relational degree of the early-warning attributes and comprehensive risk early-warning degree are then calculated. As a case study, the approach is applied to the landslide risk early-warning. The results demonstrate the rationality, feasibility, and impersonality of our approach.**

***Index Terms*—Risk Early-warning; emergency response; entropy; earthquake; matter-element model**

1. INTRODUCTION

Risk early-warning is a very complex dynamic process for earthquake emergency response [1], where the early warning object is uncertain and even unknown [2]. What affects the risk is often fuzzy and random with time-delay and other polymorphism, and often has inconsistent and even conflicting risk attributes [3, 4].

Conventional synthesis approaches to risk early-warning problems, such as Analytical Hierarchy Process, fuzzy comprehensive evaluation, principal component analysis method, and other parametric methods, are difficult in determining risk attribute weights [5-6]; while non-parametric methods, such as data envelopment analysis, are objective, but not good for comparisons among decision-making units [7].

A risk early-warning method must be able to handle the characteristics of multiple attributes, polymorphism, inconsistency, uncertainty and fuzziness in earthquake emergency response. The comprehensive integration of matter-element theory [8] and the information entropy theory [9], has been applied to solve complex decision-making problems [5]. It has the advantage of eliminating subjective attribute weight determination, and is capable of resolving contradiction and inconsistency issues. It has also been successfully applied into rock mass quality evaluation, matching evaluation systems [10] and other complex issues.

Applying the integrated method of the extension theory and entropy theory into the risk early-warning field in earthquake emergency response has advantages over other comprehensive evaluation methods. It has a unified mathematical model. In particular it extends the concept of distance in the real variable function to a range value about the early-warning attributes. Therefore, it can comprehensively evaluate the relational degree of the early-warning grade, which offers the objective, rational, accurate and scientific early-warning about the risk condition in the earthquake emergency response.

2. RISK EARLY-WARNING SYSTEM IN EARTHQUAKE

2.1 Risk Early-warning workflow in Earthquake Emergency Response

In an earthquake emergency response process, the risk early-warning workflow is to give the risk forecast about emergency response safety, integrated with geological conditions, weather environment, engineering role, emergency response, and other attributes. A risk early-warning system in earthquake emergency response is designed as shown in Figure 1.

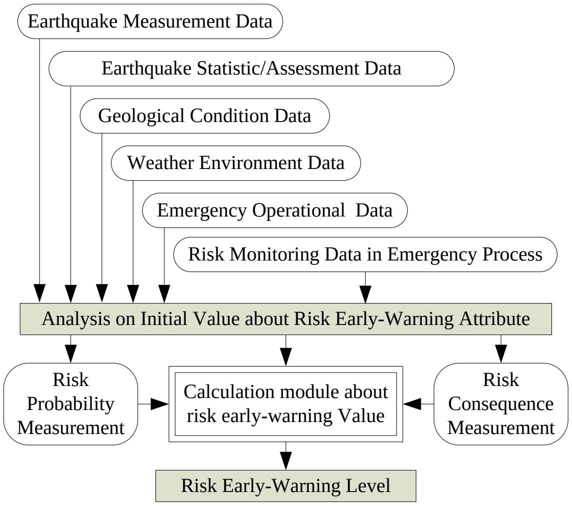

Figure 1 Risk Early-warning workflow in Earthquake Emergency Response

In Figure 1, the functions of an early warning system mainly includes forecasting likely risk, analyzing potential risk's attribute and probability, measuring its consequence, and calculating its early-warning value and grade in the earthquake emergency response.

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2.2 Risk early-warning based on entropy and matter-element model

After a clear risk early warning mission is defined, we should decide the risk early-warning grade according to the restrictions in the emergency response; identify possible risk events and their potential effects; and establish a risk early-warning index system. Figure 2 shows a risk early-warning system based on entropy and a matter-element model.

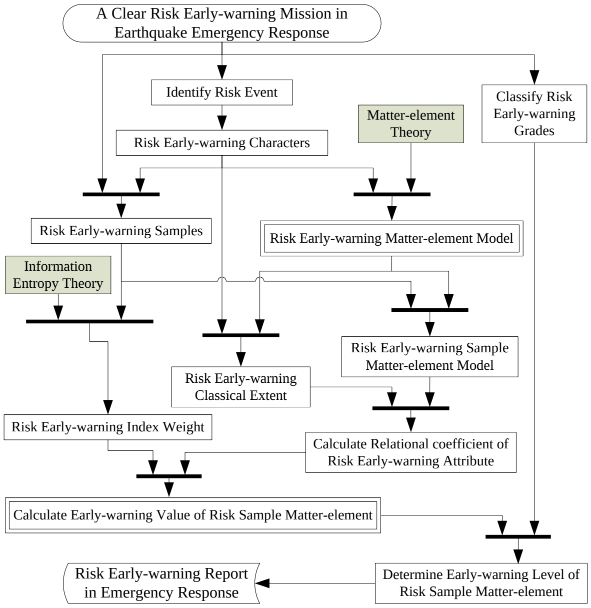

Figure 2 Risk Early-warning model based on Entropy and Matter-element model

A matter-element model refers to extending possibility and developing innovative rules and methods. It uses formal language to describe objects,events and their relationships, providing formalized method to resolve the conflicting issues. In information theory, entropy is a measure of uncertainty. It also may be the extent of a system state.

2.3 Risk Early-warning Procedure

Entropy and a matter-element model are integrated and applied into the risk early-warning operation with the following four steps.

*Step*1： Determine the risk early-warning attributes and quantify their value.

*Step*2：Determine the information entropy weight.

*Step*3： Establish the risk early-warning matter-element model and determine the relational function among the risk early-warning attributes.

*Step*4：Calculate the relational degree of single risk early-warning attribute and integrated early-warning relational degree, and then perform comprehensive assessment on risk early-warning grade.

3. ENTROPY WEIGHT CALCULATION FOR RISK EARLY-WARNING CHARACTERISTICS

3.1 Risk Early-warning Grade and Attributes

According to [11], risk early-warning grade can be classified into five levels. Let T_k be a risk grade, and T the grade set. Then

$$T = \{T_k \mid k = 1,2,..,5\} = \{\mathrm{I}, \mathrm{II}, \mathrm{III}, \mathrm{IV}, \mathrm{V}\} \quad (1)$$

Here, Ⅰ indicates the highest risk level, Ⅱ the higher risk level, Ⅲ the average risk level, Ⅳ the lower the risk level, and Ⅴ the lowest risk level.

Denote by C_i a risk early-warning attribute. The set of attributes is C , $C = [C_1, C_2, ..., C_i, ..., C_m]^T$, where m is the number of attributes.

This attribute set is of open structure. Thus, an attribute can be added into or removed from it, based on geological, engineering, environmental characteristics and the like. For example, in an earthquake emergency response process, the risk early-warning attributes may include slope angle, maximum daily rainfall, monthly total rainfall, seismic horizontal acceleration, maximum terra stress, surface deformation rate, rock structure, rock mass deformation modulus, and rock integrity coefficient[12-13].

3.2 Risk Early-warning Matter-element Event

A matter-element model is composed of event, feature attribute, and its value [14].

Let N be the risk warning event. Then, the value set V is assessed on this event N . Describe this risk event by using the matter-element method as follows:

$$R = (N, C, V) \quad (2)$$

Here, $V = [V_1, V_2, ..., V_i, ..., V_m]^T$, where V_i is the value of risk early-warning matter-element event N on the risk early-warning attribute C_i , $i = 1,2,..., m$.

3.3 Standardization of Risk Early-warning Attributes

According to the extremum change of risk early-warning attributes in an earthquake emergency response, the attributes could be divided into the *min* and *max* types. For the *min* type attributes, the lower the attributes, the lower the risk; For the *max* type attributes, the higher the attributes, the lower the risk.

Set N_j as the risk early-warning matter-element sample in the earthquake emergency response, $j = 1$,2…, n , where n is the number of samples. X_{ij} is the value of sample N_j on the early-warning attribute C_i . Then, the initial sample matrix $\tilde{R}$ is as follows:

$$\tilde{R} = \left[\begin{array}{c|cccc} C_1 & X_{11} & X_{12} & \cdots & X_{1n} \\ C_2 & X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_m & X_{m1} & V_{m2} & \cdots & X_{mn} \end{array}\right] \tag{3}$$

If C_i is a *min* type attribute, which is also called a positive effective early warning attribute, then

$$X_{ij}^{'} = [X_{ij} - \min_{1\le j\le n}(X_{ij})]/[\max_{1\le j\le n}(X_{ij}) - \min_{1\le j\le n}(X_{ij})] \tag{4}$$

If C_i is a *max* type attribute, which is also called a negative effective early warning attribute, then

$$X_{ij}^{'} = [\max_{1\le j\le n}(X_{ij}) - X_{ij}]/[\max_{1\le j\le n}(X_{ij}) - \min_{1\le j\le n}(X_{ij})] \tag{5}$$

Thus, in an earthquake emergency response, the risk early-warning sample matrix $\tilde{R}$ turns into a standard matrix $\overline{\overline{R}}$.

$$\overline{\overline{R}} = \left[\begin{array}{c|cccc} C_1 & X_{11}^{'} & X_{12}^{'} & \cdots & X_{1n}^{'} \\ C_2 & X_{21}^{'} & X_{22}^{'} & \cdots & X_{2n}^{'} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_m & X_{m1}^{'} & X_{m2}^{'} & \cdots & X_{mn}^{'} \end{array}\right] \tag{6}$$

3.4 Information Entropy Weight Calculation for Risk Early-warning Attributes

The weight of an early-warning attribute is important in the analysis of the risk early-warning system, which is quite subjective. Since it is complex, uncertain and ambiguous, it is hard to estimate it.

Entropy is a measurement for uncertain systems [15]. Based on the information entropy theory, the attribute weight is determined by the internal components and their interactions in a risk early-warning system. It is completely an objective weighting method, and the degree of information disorder could be reflected with an entropy value, which could effectively reduce subjective deviation on attribute weight.

Let f_{ij} indicate the proportion of risk early-warning event N_j on the risk early-warning index C_i.

$$f_{ij} = X_{ij}^{'} / \sum_{j=1}^{n} X_{ij}^{'} \tag{7}$$

According to the entropy calculation method of information entropy theory [9] and the specific conditions, the *Shannon* entropy value of the early-warning attribute C_i could be reckoned with the following expression.

$$e_i = H(C_i) = -\frac{1}{ln(n)} \sum_{j=1}^{n} f_{ij} ln(f_{ij}) \tag{8}$$

where e_i is the information entropy value of the risk early-warning samples in the earthquake emergency response. The larger the entropy value, the greater degree of internal disorder in the early warning system. When $f_{ij} = 0$, set $f_{ij} = 0.00001$.

At this point, in the earthquake emergency response, the weight of risk early-warning C_i can be calculated as:

$$\varpi_i = (1-e_i)/(n - \sum_{i=1}^{m} e_i) \tag{9}$$

where ϖ_i is the weight value of risk early-warning attribute C_i in the earthquake emergency response, satisfying $\sum_{i=1}^{m} \varpi_i = 1$.

4. RISK EARLY-WARNING EXTENSION MODEL BASED ON MATTER-ELEMENT METHOD

4.1 Classical and Nodal Extent of Risk Early-warning Model

Let N_{0k} be the risk early-warning standard object in earthquake-damaged emergency response on classified early-warning level T_k, and $V_{0,k,i}$ be the value range of standard object N_{0k} about the early-warning attribute $C_i, V_{0,k,i} = [A_{0,k,i}, B_{0,k,i}]$.

For early-warning attribute C_i, the value range of standard object N_{0k} is called the matter-element of the risk early-warning classical extent in the earthquake emergency response. Denote a matter-element matrix in the classical extent by R_{0k}, namely:

$$R_{0k} = \left(N_{0,k}, C, V_{0k}\right) = \begin{bmatrix} N_{0,k} & C_1 & V_{0,k,1} \\ & C_2 & V_{0,k,2} \\ & \vdots & \vdots \\ & C_m & V_{0,k,m} \end{bmatrix} = \left[\begin{array}{cc|c} N_{0,k} & C_1 & [A_{0,k,1}, B_{0,k,1}] \\ & C_2 & [A_{0,k,2}, B_{0,k,2}] \\ & \vdots & \vdots \\ & C_m & [A_{0,k,m}, B_{0,k,m}] \end{array}\right] \tag{10}$$

where $A_{0,k,i}$ is the lower limit value of the standard object N_{0k} on the early-warning attribute C_i under the early-warning level T_k, and $B_{0,k,i}$ the upper limit value, $k = 1,2,...,5$, and $i = 1,2,...,m$.

Let N_p be the nodal object, including all the standard object N_{0k} in the risk early-warning system, and the risk early-warning event, which could be converted into a standard object. Set $V_{p,i}$ as the value range of the nodal object N_p on the early-warning attribute $C_i, V_{p,i} = [A_{p,i}, B_{p,i}]$.

For early-warning attribute C_i, the value range of nodal object N_p is called the matter-element of the risk early-warning nodal extent in the earthquake emergency response. Denote a matter-element matrix in the nodal extent with R_p, namely:

$$R_p=\left(N_p,C,V_p\right)=\begin{bmatrix} N_p & C_1 & V_{p,1} \\ & C_2 & V_{p,2} \\ & \vdots & \vdots \\ & C_m & V_{p,m} \end{bmatrix}=\begin{bmatrix} N_p & C_1 & [A_{p,1},B_{p,1}] \\ & C_2 & [A_{p,2},B_{p,2}] \\ & \vdots & \vdots \\ & C_m & [A_{p,m},B_{p,m}] \end{bmatrix} \quad (11)$$

Where $V_{p,1}, V_{p,2}, \ldots$ and $V_{p,m}$ are the value ranges of the early-warning attributes C_1, $C_2, \ldots$ and C_m, or the nodal space of N_p. $A_{p,i}$ is the lower limit value of the nodal object N_p on the early-warning attribute C_i, and $B_{p,i}$ the upper limit value, $i=1,2,...,m$. Obviously $V_{0,k,i} \subset V_{p,i}$.

4.2 Calculation of Relational Function on Risk Early-warning Matter-element Event

In accordance with the risk early-warning matter-element model in the earthquake emergency response, as shown in (3), the risk early-warning event N^* is described by $R^*=(N^*,C,V^*)$ for its characteristics and their values.

$V_i^* \in V_{p,i}$ is subjected to the risk early-warning nodal extent in earthquake emergency response. According to the definition of distance, the correlation function is given in the following expression.

$$\begin{cases} \rho(V_i^*,V_{0,k,i})=\left|V_i^*-\frac{1}{2}(A_{0,k,i}+B_{0,k,i})\right|-\frac{1}{2}(B_{0,k,i}-A_{0,k,i}) \\ \rho(V_i^*,V_{p,i})=\left|V_i^*-\frac{1}{2}(A_{p,i}+B_{p,i})\right|-\frac{1}{2}(B_{p,i}-A_{p,i}) \end{cases} \quad (12)$$

Then, according to the relational function of the extension theory [14] and specific conditions, the relational coefficient of the risk early-warning matter-element event N^* to the early-warning level T_k is determined by the following expression.

$$F_k(V_i^*)=\begin{cases} \dfrac{-\rho(V_i^*,V_{0,k,i})}{\left|B_{0,k,i}-A_{0,k,i}\right|} & (V_i^* \in V_{0,k,i}) \\ \dfrac{\rho(V_i^*,V_{0,k,i})}{\rho(V_i^*,V_{p,i})-\rho(V_i^*,V_{0,k,i})} & (V_i^* \notin V_{0,k,i}) \end{cases} \quad (13)$$

Here, for the early-warning attribute C_i, $F_k(V_i^*)$ indicates the relational coefficient of the risk early-warning matter-element event N^* to the classical matter-element event $N_{0,k}$ on the early-warning level T_k, i.e., the relational degree to the k early-warning grade on the i early-warning characteristic.

4.3 Risk Early-warning Analysis

According to the relational coefficient $F_k(V_i^*)$ of the risk early-warning matter-element event N^* to the early-warning attribute C_i under the early-warning level T_k, an integrated multi-level relational degree is determined about N^* subjected to various early-warning level T_k. The early-warning value of N^* to early-warning level T_k is

$$F_k(N^*)=\sum_{i=1}^{m}\varpi_i F_k(V_i^*) \quad (1\le i\le m) \quad (14)$$

Where $F_k(N^*)$ is the relational degree of the risk warning event N^* to the classical event N_{0k} on the early-warning level T_k.

For the risk early-warning matter-element event N^*, a greater $F_k(N^*)$ indicates a higher relational degree of N^* to the early-warning level T_k. Set the following expression:

$$F_{k0}(N^*)=\max_{k}\{F_k(N^*)\} \quad (15)$$

Where $F_{k0}(N^*)$ is called the early-warning value of the risk early-warning matter-element event N^*, whose corresponding $k0$ is the relational risk level of N^*. It reflects the risk early-warning strength of this risk event N^*.

To effectively measure the risk early-warning strength of the risk early-warning matter-element event N^* in the earthquake emergency response, denote by k^* the characteristic value of the early-warning level variable for N^*. Then:

$$\overline{F_k}(N^*)=\frac{F_k(N^*)-min\{F_k(N^*)\}}{max\{F_k(N^*)\}-min\{F_k(N^*)\}} \quad (16)$$

$$k^*=\{\sum_{k=1}^{5}[k\cdot\overline{F_k}(N^*)]\}/\sum_{k=1}^{5}\overline{F_k}(N^*) \quad (17)$$

5. CASE STUDY

5.1 Initial Early-warning Data of Risk Slope Landslide Case

In emergency response to an earthquake in the area with rock slope, the risk event is potential landslide. According to the multi-layer evaluation system about the overall safety on rock slope engineering in [11], the risk classification level and its value range are given in Table 1.

Table 1: Value Range of the early-warning attribute for slope landslide emergency response

RA	*min* type Characters							*max* type Characters				
	SA	DMR	MCR	SHA	MTS	SDR	DP	RS	RMDM	RIC	C	IFA
	$/m$	$/mm$	$/mm$	$/g$	$/MPa$	$/(mm\cdot d^{-1})$		RQD	$/GPa$		$/MPa$	$/(^0)$
Ⅰ	40-90	100-150	250-300	0.20-0.40	20-25	0.20-0.40	0.8-1.0	0-30	0.0-1.5	0.05-0.15	0.00-0.05	0-13
Ⅱ	30-40	60-100	150-250	0.15-0.20	14-20	0.15-0.20	0.6-0.8	30-50	1.5-4.0	0.15-0.35	0.05-0.08	13-21
Ⅲ	20-30	40-60	100-150	0.10-0.15	8-14	0.10-0.15	0.4-0.6	50-75	4.0-7.0	0.35-0.55	0.08-0.12	21-29
Ⅳ	10-20	20-40	50-100	0.05-0.10	2-8	0.05-0.10	0.2-0.4	75-90	7.0-13.0	0.55-0.75	0.12-0.22	29-37
Ⅴ	0-10	0-20	0-50	0.00-0.05	0-2	0.00-0.05	0.08-0.2	90-100	13.0-28.0	0.75-1.00	0.22-0.32	37-45
NE	0-90	0-150	0-300	0.00-0.40	0-25	0.00-0.40	0.08-1.0	0-100	0-28.0	0.05-1.00	0-0.32	0-45

Table 2: Value of the early-warning attribute for slope landslide risk Samples

EP	SA	DMR	MCR	SHA	MTS	SDR	DP	RS	RMDM	RIC	C	IFA
N_1	21	75	260	0.16	13.6	0.09	0.23	69	2.4	0.40	0.07	27
N_2	36	21	145	0.08	16.2	0.24	0.54	53	6.8	0.21	0.19	38
N_3	11	89	245	0.12	3.7	0.04	0.39	76	7.6	0.78	0.25	25
N_4	64	28	275	0.28	6.9	0.12	0.65	28	19.8	0.66	0.16	32
N_5	52	48	230	0.06	13.4	0.31	0.82	94	4.5	0.36	0.21	8
N^*	47	18	210	0.18	4.5	0.08	0.38	22	12.3	0.59	0.13	14

Table 3: Entropy value and weight value of the early-warning attribute for slope landslide risk case

EP	SA	DMR	MCR	SHA	MTS	SDR	DP	RS	RMDM	RIC	C	IFA
Entropy	0.8365	0.7108	0.8833	0.7780	0.7671	0.7591	0.8262	0.8302	0.8790	0.8286	0.8291	0.8200
Weight	0.0726	0.1284	0.0518	0.0986	0.1034	0.1070	0.0772	0.0754	0.0537	0.0761	0.0759	0.0799

Table 4: Relational coefficient of the risk early-warning sample N^* for slope landslide risk case

EP	SA	DMR	MCR	SHA	MTS	SDR	DP	RS	RMDM	RIC	C	IFA
Ⅰ	0.14	-0.82	-0.3077	-0.1000	-0.775	-0.6	-0.5833	0.2667	-0.4675	-0.5176	-0.381	-0.0667
Ⅱ	-0.14	-0.7	0.4	0.4	-0.6786	-0.4667	-0.4231	-0.2667	-0.4029	-0.3692	-0.2778	0.125
Ⅲ	-0.2833	-0.55	-0.4	-0.1429	-0.4375	-0.2	-0.0625	-0.56	-0.3011	-0.0889	-0.0714	-0.3333
Ⅳ	-0.3857	-0.1	-0.55	-0.3077	0.4167	0.4	0.1	-0.7067	0.1167	0.2	0.1	-0.5172
Ⅴ	-0.4625	0.1	-0.64	-0.4194	-0.3571	-0.2727	-0.375	-0.7556	-0.0538	-0.2807	-0.4091	-0.6216

NOTE:
RA – Risk Grade;
SA – Slope angle;
DMR – Daily maximum rainfall;
MCR – Month cumulative rainfall;
SHA – Seismic horizontal acceleration;
MTS – Maximum terra stress;
SDR – Surface deformation rate;
DP – Drainage performance;
RS – Rock Structure;
RMDM – Rock mass deformation modulus;
RIC – Rock Integrity coefficient;
C – Cohesion;
IFA – Internal friction angle;
NE – Nodal Extent;
EP – Engineering position

Some engineering samples N_1、 N_2、 N_3、 N_4, and N_5, are obtained in the emergency response. Values of the irrelevant characteristics are expressed in Table 2, and N^* indicates the risk early-warning event.

5.2 Early-warning Value Calculation for Slope Landslide Risk Case

With the data in Table 2, risk early-warning matter-element samples are prepared. The initial risk early-warning sample data is normalized according to (4), (5), and (6). Then, the entropy value of the risk early-warning attribute is calculated with (7) and (8), as shown in Table 3.

In Table 3, the entropy value reflects the amount of the useful information, providing for the landslide early-warning system, where the "Month cumulative rainfall" takes the greatest entropy value, and its weight is 0.0518, which is the minimum weight value in the risk attributes.

Information effectiveness of the entropy measurement indicates the changing rule, which has the greater entropy value and the smaller weight value of the risk early-warning attribute. According to (12) and (13), the relational coefficient of risk early-warning sample N^* regarding the risk early-warning attribute is calculated as shown in Table 4. According to Eqs. (14), the relational degree of the risk early-warning samples regarding the early-warning level T_k is calculated as shown in Table 5.

Table 5: Relational degree and risk assessment for the slope landslide risk samples

	Ⅰ	Ⅱ	Ⅲ	Ⅳ	Ⅴ	$k0$	k^*
N^*	-0.3889	-0.2736	-0.2947	-0.0716	-0.3522	Ⅳ	3.5
N_1	-0.3733	-0.0790	-0.0766	-0.2235	-0.4535	Ⅲ	2.7
N_2	-0.3981	-0.1833	-0.2163	-0.1711	-0.3602	Ⅳ	3.1
N_3	-0.5459	-0.3874	-0.2448	-0.1246	-0.2396	Ⅳ	3.7
N_4	-0.2820	-0.3618	-0.2698	-0.1043	-0.4012	Ⅳ	3.03
N_5	-0.2469	-0.3095	-0.2711	-0.3558	-0.4437	Ⅰ	2.3

As shown in Table 5, the relational degree of the risk early-warning object N^* is $F_{k0}(N^*) = -0.0716$ on the early-warning level T_k. Then, the comprehensive early-warning value is determined as $k0 = \text{Ⅳ}$, for the risk early-warning event N^*.

According to (16) and (17), the deflection degree of the risk early-warning sample N^* is determined as $k^* = 3.5$, which indicates its risk early-warning level is Ⅳ, and its characteristic value is 3.5 as the deflection degree to the risk early-warning Ⅲ level. It means that the slope landslide is relatively safe in the general circumstance.

Base on the comprehensive risk early-warning evaluation process for the risk early-warning matter-element event N^*, the risk early-warning relational degree, risk early-warning value, and deflection degree are calculated for the samples N_1, N_2, N_3, N_4 and N_5 as shown in Table 5.

6. CONCLUSION

A new approach that integrates the risk early-warning objects, attributes and their value range into a matter-element system is proposed to study risk early-warning system's extension nature. With the formalized extension tool, the contradiction and inconsistency among the risk factors in earthquake emergency response are resolved.

With the comprehensive integration of information entropy and matter-element model, a risk event was analyzed in earthquake emergency response with full utilization of obtained information. The proposed algorithm is convenient for computer software implementation.

This proposed integrated method directly determines the weight of a risk early-warning attribute with information entropy theory, which eliminates the impact of subjective factors and makes the weight more objective.

When applying the integrated model to the risk early-warning of earthquake emergency response, besides entropy weight method for risk early warning attributes, we also need to carry on further study and improvement about relational coefficient, comprehensive early-warning value, deflection degree, and other aspects, to meet the specific risk early-warning task in earthquake-damaged emergency response process.

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