For office use only	Team Control Number	For office use only
T1 ____________	**89408**	F1 ____________
T2 ____________		F2 ____________
T3 ____________	Problem Chosen	F3 ____________
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Summary Sheet

A Model for State's Fragility Assessment Based on the Climate Impact

In order to assess the climate impact on the fragility of a state, we establish a fragility index evaluation model and a prediction model. We analyze the ways that climate affects fragilities of Afghanistan and Indonesia separately according to sensitivity analysis. For Indonesia, we utilize the prediction model to predict its trend of the fragility. Finally, we modify the models according to the size of the targets.

For task one, we construct a fragility index evaluation model. We select four Tier 1 indicators and 17 Tier 2 indicators and utilize the Analytic Hierarchy Process to calculate the fragility under normal and adverse climate conditions. Then we sum the two scores weighted by happening probability and take it as the final fragility score. Based on the analysis of 19 countries' data, we decide three levels of fragility index.

For task two and three, we select Afghanistan and Indonesia as targets. Then, we conclude the impact of climatic factors on the fragility index according to sensitivity analysis. In addition, we also conclude that if the proportion of disaster days throughout the year increases, the state's fragility will significantly increase correspondingly. For Indonesia, we use Principal Component Analysis to reduce the dimensionality of its data over the last ten years. Then we put the data into the BP neural network and find that Indonesia will not be a fragile state in the next ten years.

For task four, according to sensitivity analysis, we find that the number of refugees has a greater impact on the fragility index. So our plan is to set up relief stations. When calculating the cost, we first evaluate the cost and effectiveness of each building site. Then we bring the model into the 0-1 programming model to find the optimal solution by using the Simulated Annealing algorithm.

For task five, in the case of smaller "states", we take the impact of neighboring "states" into consideration. As for larger "states", through cluster analysis of countries all over the world, we calculate the inner closeness of "state" to amend the model.

Last but not least, we discuss the advantages and disadvantages of the model and propose some optimization directions.

Keywords: Fragility; Climate; AHP; Back Propagation; PCA

1 Introduction

There are about two hundred states in the world, some of them are socially peaceful, while others are in turbulent turmoil. Since 2006, the World Bank Group's (WBG) Fragile, Conflict and Violence Group has annually released the Harmonized List of Fragile Situations. And according to the newest research, we find that the climate change has a huge influence on the state's fragility. Therefore, it is quite important and necessary to consider a solution to mitigrate a state's fragility.

In a variety of effective ways to solve such assessment problems, Analysis Hierarchy Process(AHP) is an effective method. It divides the research object into several layers as a system, and the weight setting of each layer will directly or indirectly affect the result. After comparing the quantitative relationship between elements of the same level and elements of the next level, a simple math method is carried out. Therefore, Analysis Hierarchy Process has the potential to assess the fragility of a state.

Our group tries to build a model which can identify when a state is fragile, vulnerable or stable and can also identify how climate change increases fragility of a state directly or indirectly.

2 Nomenclature

Abbreviation	Description	Unit
GDP	Gross domestic product per capita	hundred million yuan
CE	CO2 emissions	kiloton
PM 2.5	PM 2.5 index	%
TC	Temperature change	℃
AGGR	Annual GDP growth rate	%
CEPG	CO2 emissions per unit of GDP	kg/$
STJA	Scientific and technical journal articles	thousand
EI	Economic inequality index	none
SED	Secondary education number	thousand
RP	Refugee population	thousand
DP	Demographic pressures	none
TL	Talent loss	none
PS	Public services	none
HR	Human rights	none
SL	State legitimacy	none
IPI	Interstate's peace index	none
SPI	Social peace index	none

3 Assumptions

In order to have a better study on this paper, we simplify our model by the following assumptions:

- Assuming that there is no change in the political parties in the country and no events like reforms occur.
- Assuming that there will be no such thing with a small probability as a war.
- Assuming that the evaluation results of the judgment matrix in the model are universal and ignoring the special cases of individual countries.
- Assuming that except for the variables in the index system in this article, other factors that may affect the fragility remain unchanged.
- Assuming that all governments are aware of the specific cost of infrastructure such as relief stations in their own country. What needs to be determined is only the construction plan.

4 Problem Analysis

For task one, we need to establish the fragility index evaluation model first. In this model we can get an index F which is used to describe the fragility of a state. According to this model, we should divide the fragility index into three levels to show when a state is fragile, vulnerable or stable. And then, we should conclude the impact of climatic factors on the fragility index. The results of task one refers to Establishment of Model and Validation of Model.

For task two, we choose Afghanistan, one of the top 10 most fragile states and find out the related data. We use the fragility index evaluation model that we have built in task 1 and substitute the data into the model to calculate the fragility index. Then we can conclude in what ways Afghanistan may be less fragile through sensitivity analysis. The results of task two refers to Establishment of Model and Validation of Model.

For task three, we choose Indonesia and find out the related data. We use the fragility index evaluation model that we have built in task 1 to calculate the fragility index in the last ten years. After data processing, we can predict the fragility index in the next few years. And it may help us find when a state will reach a tipping point. The results of task three refers to Establishment of Model and Validation of Model.

For task four, we make sensitivity analysis first and find out the three most important factors when climate changes. Then we choose one to make a policy to reduce it. After that, we predict the total cost of this policy. The results of task four refers to Establishment of Model and Validation of Model.

For task five, we should check whether our model can work on a city or a continent. And then, we will make some changes to modify the model. The results of task four refers to Modification of Model.

5 Establishment of Model

5.1 State's fragility evaluation model

This model can be divided into two parts. One is for assessing state's fragility in the absence of a climate disaster and the other is for assessing state's fragility after a climate disaster. Then based on the happening probability of two models, a comprehensive state's fragility score is concluded.

5.1.1 Evaluation of state's fragility in the absence of a climate disaster

For this part, we select all the indicators needed for evaluation and establish a reasonable evaluation index system. Then we build the state's fragility evaluation model based on the index system.

5.1.1.1 The establishment of evaluation index system

A sound index system is the basis of a reasonable evaluation. Here are some principles to follow when selecting indicators.

1) Comprehensiveness: The index system should fully reflect the political, economic, social and climatic conditions of a state.

2) Typicality: The indicator system should reflect the characteristics and causes of the state's fragility. The evaluation indicators at all levels should reflect the key elements of fragility.

3) Operability: Taking account of the efficiency, accuracy and credibility of data acquisition, selection of indicators should make sure that data collection is not too hard.

4) Universality: In order to ensure the applicability of the model, the indicator should use interstate's common names whenever possible and ensure the credibility of the data.

At present, PSR model[1] (Pressure-State-Response) is the most commonly used in the study of state's fragility. According to this model, we consider the following indicators.

The first are the pressure indicators, reflecting the impact of climate change and human activities. We choose PM 2.5 air pollution, CO_2 emissions, temperature change as indicators in climate aspect. As for human activities, we choose annual GDP growth rate as an evaluation indicator.

The second are the state indicators, reflecting the general situation of all aspects of the state, including the overall economic level, people's living standards, social services and so on. We select GDP, refugee population, demographic pressures talent loss, public services, interstate's peace index and social peace index.

The third are the response indicators, reflecting the state’s adaptive capacity of responding to the changes caused by nature and human activities. We choose human rights, state legitimacy, CO_2 emissions per unit of GDP, number of scientific and technical journal articles, economic inequality and secondary education number.

Finally, based on the analysis above, we have completed the establishment of the indicator system. After the merge of similar indicators, we get the framework of the indicator system as shown in the figure 1. There are four Tier 1 indicators and 17 Tier 2 indicators corresponding to them.

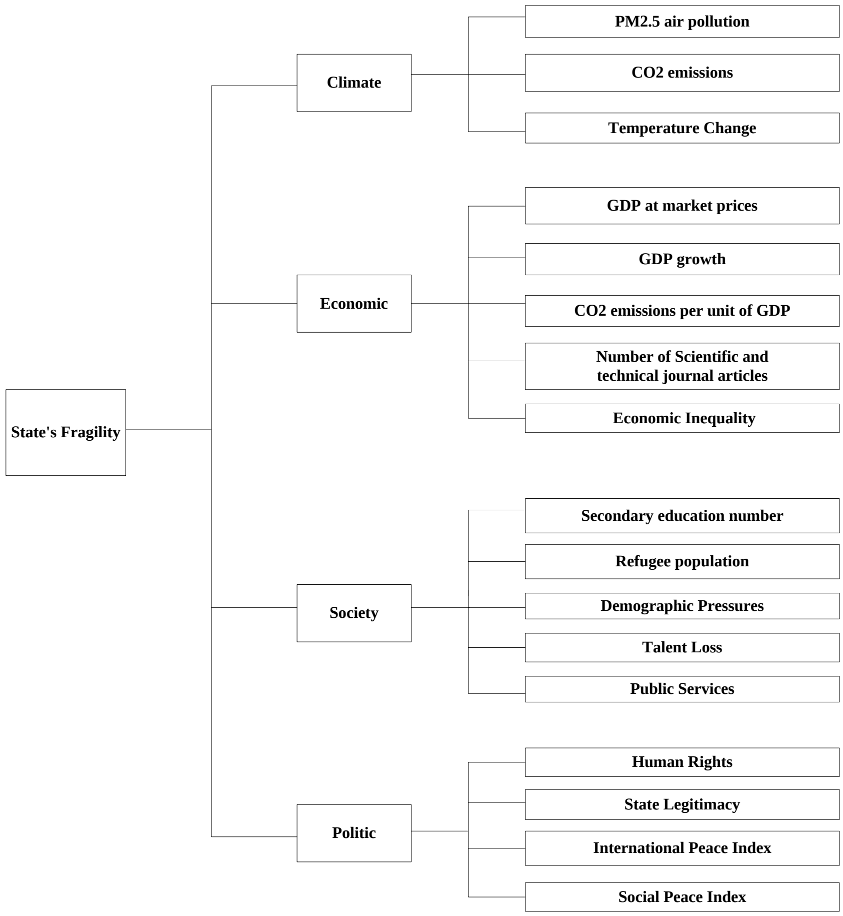

Figure 1: The indicator system

5.1.1.2 Standardization of raw data

Considering that the dimensions of the original data are different and some data is positively related to the evaluation target while others are negatively related to the target, it is necessary to standardize the original data for the further modeling. Here we define that the more fragile countries are, the greater the fragility index value will be.

For the indicators whose value is positively related to the evaluation target, we use the non-dimensional treatment to standardize data. The specific expression is as follows:

$$D_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 9 + 1$$

where X_i represents the raw data, X_{min} represents the minimum value of these data, X_{max} represents the maximum value of these data. Obviously, after processing, each value is in the interval [1,10].

For the index whose value is negatively correlated with the evaluation target, do the same chemotaxis and non-dimensional treatment, the specific treatment is as follows:

$$D_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 9 + 1$$

5.1.1.3 Determine the weight of the indicators by Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) has been applied in various fields as a comprehensive evaluation method combining qualitative analysis and quantitative analysis. It is based on the nature of the problem and the general goal to be achieved. It divides the problem into different components. According to affiliation and the interrelationship between factors, the indicators are combined to form a multi-level analysis structure model. The problem is thus transformed into the determination of the relative weight of the indicators.

The flow chart of AHP is as follows:

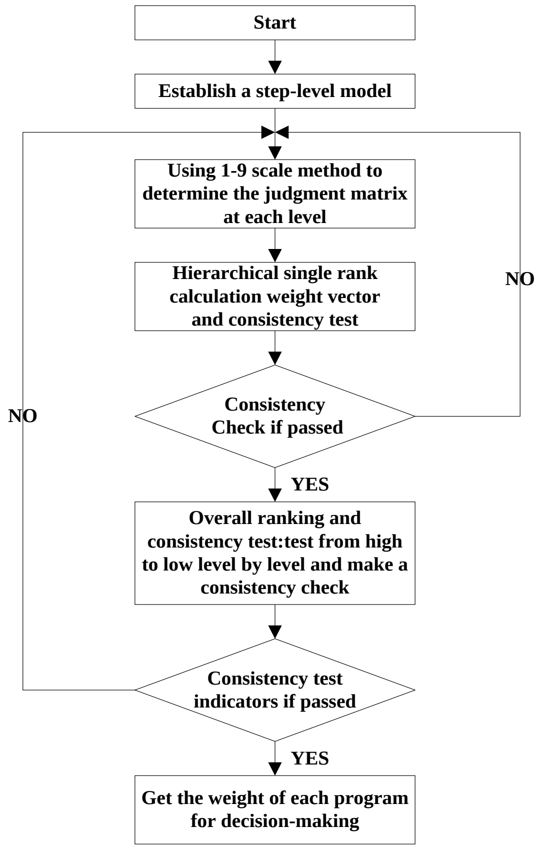

Figure 2: The flow chart of AHP

The relative importance of the indicators can be scored according to the following nine-scale method.

Table 1: The meaning of 1 to 9 scale

Scale	Importance comparison results
1	The two elements are of equal importance
3	The former is slightly more important than the latter
5	The former is obviously more important than the latter
7	The former is strongly more important than the latter
9	The former is extremely more important than the latter
2,4,6,8	The middle value of the above adjudication

Based on the evaluation index system established in the previous section, we construct the judgment matrix of the Tier 1 indicators. In assessing the significance of Tier 1 indicators, we reviewed a large number of documents related to state's fragility assessment[2][3] and reached the following conclusions:

Economy is the most important indicator among the four Tier 1 indicators. The overall social situation such as social equity is slightly less important than the economic factor. And the influence of political factors is second to social factors but they sometimes have equal importance. Finally, climatic factors have less influence than other factors. Based on the above analysis, the results can be expressed in table 2.

Table 2: Judgments of Tier 1 indicators

	economy	society	politics	climate
economy	1	1	2	3
society	1	1	2	3
politics	1/2	1/2	1	2
climate	1/3	1/3	1/2	1

Then we have the judgment matrix A

$$A = \begin{pmatrix} 1 & 2 & 2 & 3 \\ \frac{1}{2} & 1 & 2 & 3 \\ \frac{1}{2} & \frac{1}{2} & 1 & 2 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix}$$

We use the consistency test method proposed by Saaty. Calculate CI and do the following steps.

$$CI = \frac{\lambda - n}{n - 1}$$

The procedure is constructing a random matrix A' to calculate the value of CI and then calculate CR based on the data in the following table and expression.

Table 3: RI value table

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

where

$$CR = \frac{CI}{RI}$$

If $CR < 0.1$, it means the data get through the consistency test.

According to our matrix , we use MATLAB to calculate the eigenvalues and the corresponding eigenvectors. Then we obtain the following results

$$\lambda = 4.0458$$

$$\mathbf{w} = (0.41549, 0.29259, 0.18495, 0.10697)$$

The consistency index $CI = 0.015273$, then $CR = 0.01697 < 0.1$, which passes the consistency test. Therefore, the relative weights of economic, social, political and climatic indicators can be determined as 0.41549, 0.29259, 0.18495 and

0.10697. In the same way, constructing the judgment matrix corresponding to each Tier 2 index can obtain the following Tier 2 index judgment matrix.

$$B_1=\begin{pmatrix}1 & 1 & 2 & 3 & 4\\ 1 & 1 & 2 & 2 & 3\\ \frac{1}{2} & \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{3} & \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 1\end{pmatrix}\quad B_2=\begin{pmatrix}1 & 2 & 3 & 3 & 4\\ \frac{1}{2} & 1 & 1 & 2 & 3\\ \frac{1}{3} & 1 & 1 & 1 & 2\\ \frac{1}{3} & \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 1\end{pmatrix}$$

$$B_3=\begin{pmatrix}1 & 2 & 2 & 2\\ \frac{1}{2} & 1 & 1 & 1\\ \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{2} & 1 & \frac{1}{2} & 1\end{pmatrix}\qquad B_4=\begin{pmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{pmatrix}$$

Among them, B_1, B_2, B_3, B_4 are the judgment matrix of economic, social, political and climatic indicators. Calculated in the same way as the Tier 1 indicators, the weights of the Tier 2 indicators shown in the following table are obtained.

Table 4: The weights of the Tier 2 indicators corresponding to Tier 1 index

	B_1	B_2	B_3	B_4
the ratio vectors **w**	0.33412	0.15994	0.39521	0.33333
	0.14000	0.40559	0.19760	0.33333
	0.15296	0.13855	0.23902	0.33333
	0.08128	0.07952	0.16817	
	0.29000	0.21640		

All the data above has passed the consistency test.

The final weight of each Tier 2 index is the weight corresponding to Tier 1 index multiplied by the weight of Tier 1 index. Finally, the weights for all the indicators are shown in the following table

Table 5: The weights for all the indicators

Tier 1 indicators	Relative weight	Tier 2 indicators	Relative weight	Final weight of Tier 2 indicators b_i
climate	0.10791	*PM2.5*	0.33333	0.03597
		CE	0.33333	0.03597
		TC	0.33333	0.03597
economy	0.48036	*GDP*	0.33412	0.16050
		AGGR	0.14189	0.06816

		CEPG	0.15296	0.07348
		STJA	0.08128	0.03904
		EI	0.28975	0.13918
society	0.21582	*SED*	0.15994	0.03452
		RP	0.40559	0.08753
		DP	0.13855	0.02990
		TL	0.07952	0.01716
		PS	0.21640	0.04670
politics	0.19591	*HR*	0.39521	0.07742
		SL	0.19760	0.03871
		SPI	0.23902	0.04683
		IPI	0.16817	0.03295

5.1.1.4 State's fragility score results

After determining the weight of each indicator in the score, multiplying the data standardized by each indicator and summing, the comprehensive fragility score of the state can be obtained as follows.

$$F_1 = \sum D_i \cdot b_i$$

where D_i represents the standardized Tier 2 index, b_i represents the final weight of each Tier 2 index. F_1 represents the state's fragility score.

5.1.2 State's fragility after a climate disaster

The main idea of modeling is still the same as above, except that the value of judgment matrix differs.

By consulting a large amount of documents[4][5][6], we find that when the climatic conditions change significantly, the influence of the political factors will exceed the social ones. Therefore, the judgment matrix needs to be re-determined. The judgment results of the Tier 1 indicators are shown in the following table:

Table 6 : Judgments of Tier 1 indicators

	economy	society	politics	climate
economy	1	1	2	3
society	1/2	1	2	3
politics	1/2	1/2	1	2
climate	1/3	1/3	1/2	1

$$A=\begin{pmatrix}1 & 1 & 2 & 3\\ 1 & 1 & 1 & 2\\ \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 1\end{pmatrix}$$

The Tier 2 indicator judgment matrix B_2 turns into

$$B_2=\begin{pmatrix}1 & 3 & 4 & 4 & 5\\ \frac{1}{3} & 1 & 2 & 2 & 3\\ \frac{1}{4} & \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{4} & \frac{1}{2} & 1 & 1 & 2\\ \frac{1}{5} & \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 1\end{pmatrix}$$

Other Tier 2 indicator judgment matrices does not change. Other calculation steps are the same as before.

After calculation, we can get the distribution of the evaluation weights when the climatic conditions are adverse as is shown in the following table.

Table 7: The weights for all the indicators

Tier 1 indicators	Relative weight	Tier 2 indicators	Relative weight	Total weight of Tier 2 indicators b'_i
climate	0.12381	*PM 2.5*	0.33333	0.04127
		CE	0.33333	0.04127
		TC	0.33333	0.04127
economy	0.36586	*GDP*	0.33412	0.12224
		AGGR	0.14189	0.05191
		CEPG	0.15296	0.05596
		STJA	0.08128	0.02974
		EI	0.28975	0.10601
society	0.23256	*SED*	0.12198	0.02837
		RP	0.46241	0.10754
		DP	0.12960	0.03014
		TL	0.0713	0.01660
		PS	0.21463	0.04991
politics	0.27777	*HR*	0.39521	0.10978

	SL	0.19760	0.05489
	SPI	0.23902	0.06639
	IPI	0.16817	0.04671

The result is similar to F_1

$$F_2 = \sum D_i \cdot b'_i$$

where, D_i represents the standardized Tier 2 index, b_i represents the final weight of each Tier 2 index. F_2 represents the state's fragility score.

5.1.3 State's fragility

According to the analysis above, we respectively obtain the fragility scores of a state when it is normal or affected by climate disasters. Obviously, the coexistence of two fragility scores will cause trouble to further analysis so we consider to combine two scores to get a single score.

We consider doing a linear overlay. The problem lies in the selection of overlay coefficient. It should at least has the following properties.

1) It is related to α. α represents the proportion of disaster days throughout the year.
2) $k_2 + k_1 = 1$, where k_1 represents the overlay coefficient of F_1 and k_2 represents the overlay coefficient of F_2.
3) When $\alpha = 0,\ k_2 = 0$; When $\alpha = 1,\ k_2 = 1$
4) α and k_2 are positively correlated and $\frac{d^2 k_2}{d\alpha^2} > 0$. Because the adverse effects of a concentrated bad weather will be higher than the impact of the same amount of time but relatively fragmented weather.

Considering the four requirements above, we structure the following value.

$$k_1 = e^{\frac{\alpha}{\alpha-1}}$$

$$k_2 = 1 - e^{\frac{\alpha}{\alpha-1}}$$

So the overall rating is

$$F = k_1 F_1 + k_2 F_2 = e^{\frac{\alpha}{\alpha-1}} \times \sum D_i \cdot b_i + (1 - e^{\frac{\alpha}{\alpha-1}}) \times \sum D_i \cdot b'_i$$

where F represents the state's fragility score.

5.1.4 Fragility levels

Based on the scores of each state's fragility, according to the grading from the reference links[7], we get the corresponding scoring range of each level of fragility. The results refer to Validation of Model.

5.2 Fragility prediction model

This model predicts the time it takes for a state to reach the tipping point as the state's fragility index changes over time. The model consists of two parts: the Principal Component Analysis and the BP neural network. We use the PCA to reduce the dimension of the data and then get three comprehensive indicators. We next take the principal component data vector of each year as input and the fragility index as output to train the neural network to predict the future trend of fragility index. The model's frame is shown in the figure 3.

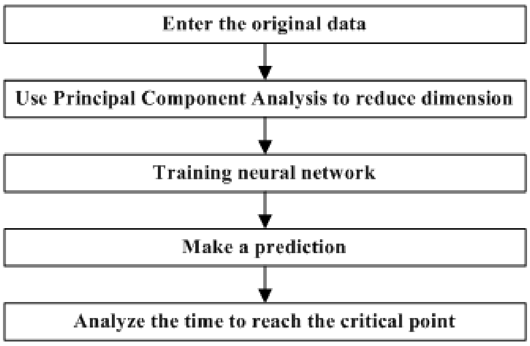

Figure 3: The fragility prediction model's frame

5.2.1 Establish BP neural network

We establish a three-level BP neural network, including the input layer, the hidden layer and the output layer. The upper and lower layers are fully connected while there is no connection between the neurons of the same layer. Structure of BP neural network is shown in the figure. The weights of the network between the input layer neurons and the hidden layer neurons reflect the connection strength between the two neurons. When the learning sample is provided to the input neuron, the neuron's output value is passed through the hidden layer to the output layer. The result received by the output layer is reversely passed through the hidden layer back to the input layer according to the decrease of the error, so that the weight of each connection is gradually amended. As the correction of error backpropagation repeatedly proceeds, the correct rate of response of the network to the input is also rising. Finally, when the error is reduced to the desired range, training is completed and predictions can be made.

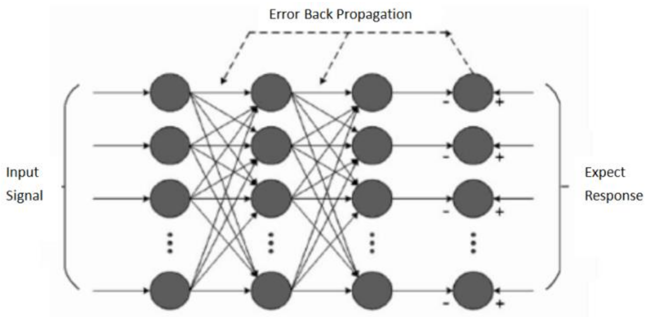

Figure 4: Structure of BP neural network

5.2.2 Principal Component Analysis

Due to the large number of indicators in the evaluation system and the mutual correlation between them, the information reflected by the indicators overlap to a certain extent, which affects the processing of the model. Therefore, we process the original data by Principal Component Analysis, replacing the original indicators with fewer and unrelated comprehensive indicators without losing information, and carry out weighted synthesis according to the contribution rate of each comprehensive indicator evaluation. The Principal Component Analysis process steps can refer to the following flowchart.

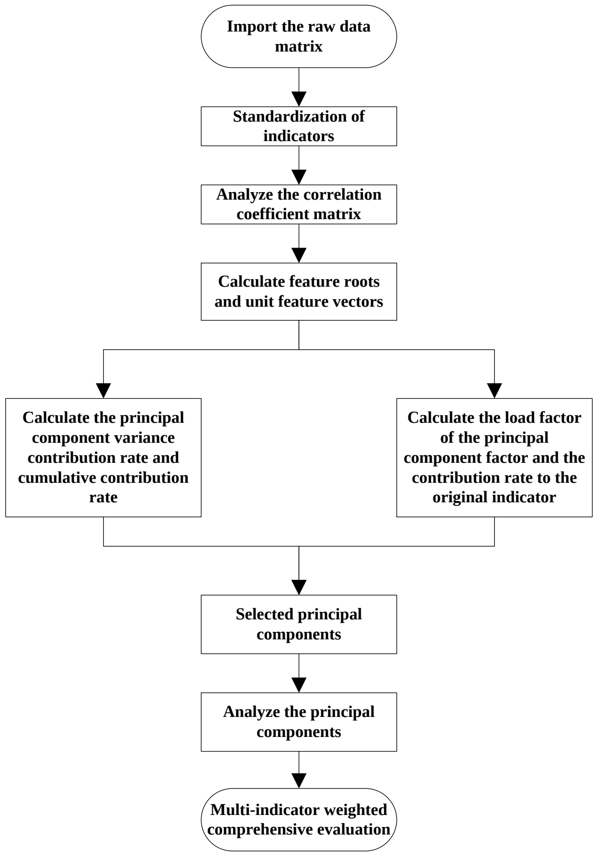

Figure 5: The Principal Component Analysis process steps

5.3 Cost estimation model

Based on the problem analysis section, this section is used to build a model of estimating state's intervention costs.

The number of refugees in the state can be effectively reduced through the establishment of relief stations. States may consider setting up relief stations in areas where the refugee population reaches more than 5% of the local population. First of all, it is necessary to make an estimate of the cost of establishing relief stations and the number of people who can afford relief.

The cost of setting up a relief station C_i is positively related to the sum of construction manpower costs per square meter w_i, construction materials costs and long-term maintenance costs m_i. The area of relief stations built is positively related to the density of refugees (ratio of the number of refugees n_i and the square of the area s_i). By asking a local relief station construction costs, calculate the proportionality coefficient k=214.97.

$$C_i = k\frac{n_i}{s_i}\times(w_i + m_i)$$

The effectiveness of relief stations will be reduced as the population of the refugees increases. Therefore, the number of relief workers needs to be amended by a index of $k_{ri} = 1 - e^{-n_i}$ so that the number of refugees who can be helped by the local relief stations can be expressed as

$$N_i = k_{ri} n_i$$

Using the fragility assessment model, we can calculate the total number of refugees who will need to make the state less stable.

$$N = \frac{F_0 - F_{target}}{weight}$$

In order to achieve the expected number of relief and make cost as little as possible, we need to make a decision on the location of the relief station. Based on the conditions that we known, we can establish a 0-1 planning model as follows:

$$Min \quad \sum_i y_i C_i$$

$$s.t. \quad \begin{cases} \sum_i y_i N_i \geq N \\ y_i = \mathbf{0} \quad or \quad 1 \end{cases}$$

where y_i represents whether a relief station in the program is open. If open, y_i=1. Otherwise, y_i=0.

At this point, we can find the optimal solution of the model by utilizing simulated annealing algorithm

6 Validation of Model

6.1 State's fragility Assessment Model

6.1.1 State's fragility level

Based on the reference site attached to the competition title, we obtained the Interstate's fragility Index Distribution Table shown below. We will use this table as a benchmark to rate our rating state's fragility assessment model.

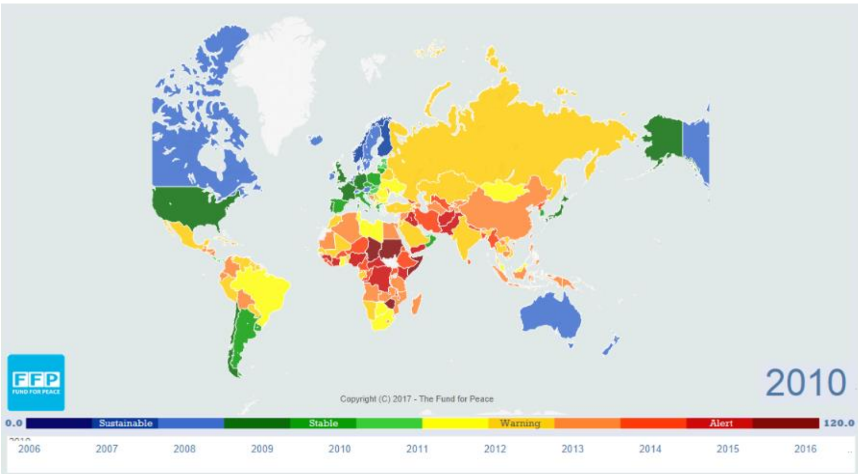

Figure 6: Interstate's fragility index distribution table

Considering the convenience of data acquisition, we collected 2010 data of 19 states with different stages of development. The original data refers to the appendix G. The source of the data is from

http://www.worldbank.org/en/topic/fragilityconflictviolence/brief/harmonized-

list-of-fragile-situations
and http://www.fao.org/faostat/en/#data/ET

Based on the state's fragility assessment model, combined with the level of fragility shown in the graph, we obtain the following data.

Table 8: Fragility score results

State	Fragility index F	Colours in Figure 6
Democratic Republic of the Congo	8.0489	
Sudan	7.7729	
Chad	7.5927	
Afghanistan	7.3512	
Côte d'Ivoire	7.3318	
Iraq	7.1158	
Thailand	6.3837	
Indonesia	6.0871	
Malaysia	5.9243	
Turkey	5.7145	
Brazil	5.4346	
Poland	5.0025	
Argentina	4.4922	
Germany	4.3217	
Italy	4.2105	
United States	3.7852	
United Kingdom	3.6555	
Singapore	3.4368	
Australia	3.0041	

From the table above, we can see that the state's fragility assessment model we established basically agrees with the evaluation results of this website. The only obvious difference is the situation of Singapore. According to our model, Singapore is more adaptable than most states while the webpage divides it into Warning levels. After reviewing the data on the webpage score, we found that Singapore ranked the 160th among the states in terms of state's fragility (a total of 177 states and regions are ranked. The more advanced, the more fragile the state). It's obvious that Singapore does not belong to the warning level, so the web data processing results in Singapore is not convincing. Excluding Singapore, the controversial data, the other data trends are consistent.

Based on the table above, we divide the state's fragility into three levels. States with a fragility score above 7 are in the fragile states, states with a score below 5 are in stable states and states with a rating in the range of 5 to 7 are in the vulnerable states. The results are expressed in the following table:

Table 9: Table of state's fragilities

Grading interval	Evaluation results
Greater than 7	fragile
5-7	vulnerable
Less than 5	stable

6.1.2 Fragility assessment to Afghanistan

In the top 10 of the Fragile State Index, we chose Afghanistan as our research object.

The 19 countries are still selected as the overall data environment. According to the national fragility assessment model, the following is rating results.

$$F_1 = 7.1430$$
$$F_2 = 7.5594$$
$$F = 7.3512$$

The results show that Afghanistan is a fragile country with a rating of 7.3512. The impact of climate on the fragility of Afghanistan will be divided into direct and indirect impacts.

Direct impact is through climate indicators in the AHP to reflect. The climate sensitivity-related factors are calculated as shown in the table below

Table 10: Sensitivity analysis

Index	Relative rate of change of indicators	F_1 Relative change	F_2 Relative change	F Relative change
PM 2.5	5%	0.3744%	0.4296%	0.3909%
	10%	0.7488%	0.8591%	0.7819%
CE	5%	0.0412%	0.0473%	0.0430%
	10%	0.0824%	0.0945%	0.0860%
TC	5%	0.1085%	0.1245%	0.1133%
	10%	0.2172%	0.2492%	0.2268%

According to the conclusion of the sensitivity analysis, as the Tier 1 indicators, the climatic factors have a direct impact on the state's fragility. It can be seen that the changes of *PM* 2.5 and *TC* indicators are relatively large for Afghanistan.

The indirect impact of climate on the fragility of Afghanistan is reflected in the values of weights k_1 and k_2 and the size of F_1 and F_2. First, the value of F_2 is significantly greater than the value of F_1, which means that in our model the worse the climate, the more fragile the country. Second, the severity of the climate is reflected in the proportion of bad weather time. According to the expression $k_2 = 1 - e^{\frac{\alpha}{\alpha-1}}$, the worse the climate, the higher the k_2, the higher the sensitivity of F_2 to the final score F. This reflects that the greater the value of F, the more fragile the country.

The following table shows the differences between the indicators of F_1 and F_2.

Table 11: Differences between indicators of F_1 and F_2

Indicators affected by climate change significantly	the weight of normal weather	the weight of adverse weather

RP	0.08753	0.10754
DP	0.02990	0.03014
PS	0.04670	0.04991
SPI	0.04683	0.06639
IPI	0.03295	0.04671

It can be seen from the table that in a harsh climate, the weights of *RP*, *DP*, *PS*, *SPI* and *IPI* increase, which reflect the state's fragility in the case of disaster more objectively.

6.1.3 Fragility assessment to Indonesia

For countries that are not in the top 10 list, we select Indonesia as the target for analysis.

The 19 countries are still selected as the overall data environment. According to the state's fragility assessment model, the following is rating results.

$$F_1 = 5.9507$$
$$F_2 = 6.2235$$
$$F = 6.0871$$

The result shows that the current state's fragility rating of Indonesia is 6.0871, which belongs to the vulnerable countries. Similarly, the impact of climate on Indonesia's fragility will be divided into immediate and indirect impacts. The impact is similar to the previous analysis of Afghanistan. The specific ways in which the climate makes it more vulnerable refer to the analysis of the weights of the Tier 2 indicators in the previous section.

Here we focus on analyzing the reason why Indonesia is less vulnerable than Afghanistan. The indirect impact of fragility is reflected in the coefficient of k_2 and the size of F_1 and F_2. According to the evaluation model, the indicators of Indonesia make the difference between F_2 and F_1 small, smaller than that of Afghanistan. In other words, the impact of bad weather on Indonesia itself is smaller than that of Afghanistan. This is determined by Indonesia's three other Tier 2 indicators in addition to climate.

6.2 Fragility prediction model

6.2.1 Validation of Model

The test of this model is based on data from Indonesia, see appendix G. The results of the principal component analysis are shown in the following table.

Table 12: The results of the principal component analysis

Ingredient	% of Variance	Cumulative %
1	68.78	68.78
2	19.56	88.34
3	7.77	96.11

We can see that these three components have accumulated 96.11% of the contribution rate. Therefore, these three component data can reasonably and effectively reflect the fragility of Indonesia. The following table shows the data of the main components of each year.

Table 13: The data of the main components of each year

Ingredient	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	4.77	2.67	2.14	2.37	1.92	0.89	-0.27	-1.46	-2.33	-3.16
2	1.96	1.02	0.34	-0.42	-0.79	-1.56	-1.14	-1.64	-2.14	0.17
3	2.13	-0.91	-1.55	-0.13	-0.87	-0.39	0.4	0.72	0.69	0.34

Put the processed data and the score of every year's fragility to the neural network for training. The results are shown in the figure 7 and the table 14:

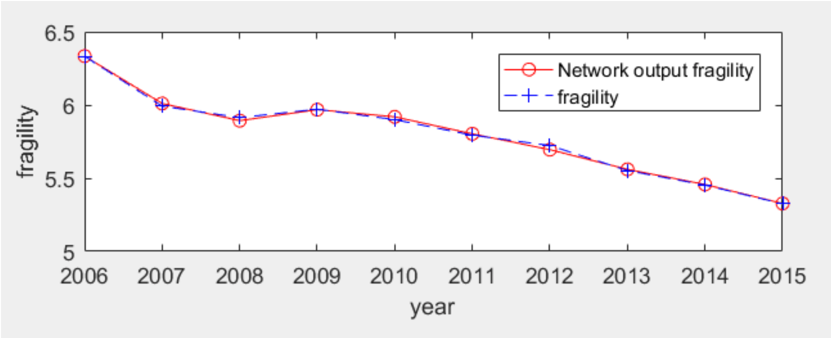

Figure 7: The results of neural network

Table 14: The results of neural network

Year	2016		
Score	Real Values	Estimated Values	Absolute Value of Relative Error/%
	5.3180	5.3126	0.10
Year	2017		
Score	Real Values	Estimated Values	Absolute Value of Relative Error/%
	5.1762	5.1944	0.35

From the data error analysis in the table, the prediction error of the established neural network is less than 0.5% and the accuracy has reached the expectation. It can be considered that the neural network has completed the training requirements.

6.2.2 Forecast based on fragility prediction model

Using the well-trained neural network, the state's fragility of the next 10 years is predicted and the predicted results are shown in the figure 8 and the table 15.

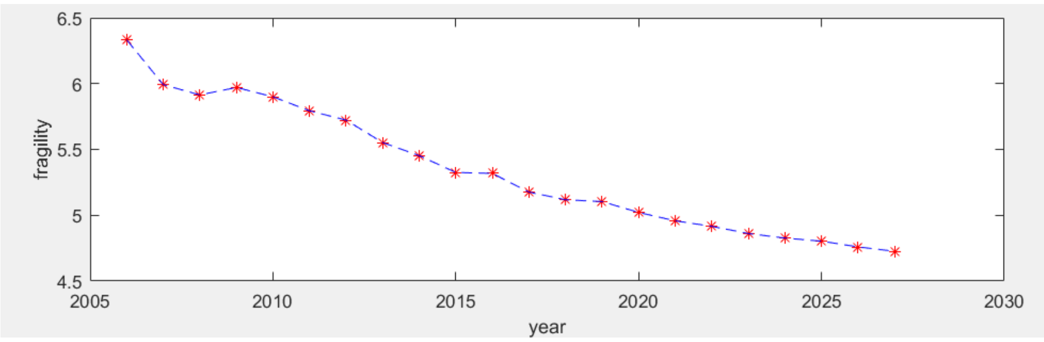

Figure 8: The results of neural network

Table 15: The results of neural network

year	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Fragility	5.118	5.104	5.021	4.958	4.916	4.861	4.827	4.803	4.759	4.726

From the predicted data, we can see that under the premise of not considering the change of external factors other than the indicators, Indonesia's fragility is decreasing year by year and will never reach the critical point. The critical point is based on the level of fragility, which has been discussed above.

6.3 Solution to cost estimation model

Firstly, we introduce the Simulated annealing (SA). SA is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space. It is often used when the search space is discrete (e.g., all tours that visit a given set of cities). For problems where finding an approximate global optimum is more important than finding a precise local optimum in a fixed amount of time, simulated annealing may be preferable to alternatives such as gradient descent.

Due to the lacking of time, the corresponding data has not yet been found, so we make up some data to verify the feasibility of the model:

Table 16: The cost and the number of the refugee in potential sites of relief station

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
cost	514	471	1348	475	369	1107	213	687	541	864	779	418
refugee	4.3	5. 1	13.5	3.9	2.5	5.4	1.2	4.8	3.5	7.7	10.4	6.5

The number of refugees expected to be able to get help is 54.3 thousand.

Bring this set of data into the model and implement it with Simulated Annealing algorithm. Then we get the optimal solution to set up a relief station and set up the total cost.

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
set	1	0	1	1	0	0	0	1	1	1	1	1

Finally, we get that the estimated total cost is 5,612 thousand dollars.

7 Modification of the model

7.1 For larger "states" (such as continents)

For a continent, due to the different levels of cooperation or conflicts between countries, the evaluation model of the state's fragility needs to be modified in order to evaluate the fragility of continents. The main direction of revision is to add indicators that reflect the inner closeness of continents to the Tier 1 indicators.

Because relations between countries are difficult to quantify and have to do with economics, politics and history, it is unreasonable to study the closeness on the basis of each country. Therefore, we consider clustering the various countries in the world based on the overall situation. On the basis of cluster analysis, we analyze the proportion of each type of state within each continent and measure the internal level of each continent with the largest proportion.

Next is to provide one kind of cluster analysis.

Taking into account that the indicators of clustering should reflect the degree of development, the degree of contact with other countries and the fragility of the country, we select the GDP per capita, the total volume of imports and exports and the state's fragility of each country as a classification indicator to carry out K -Means cluster analysis. The process is as follows:

① Because K-Means clustering analysis is sensitive to the initial cluster centers, we select the following four countries as cluster centers: the United States, China, Bangladesh and Sudan.

② Cycle ③ to ④ until each cluster no longer changes.

③ According to the average of each clustering object (center object), calculate the distance between each object and these center objects and re-divide the corresponding objects according to the minimum distance.

④ Recalculate the average of each cluster (center object), until the cluster center no longer changes. This division minimizes the following formula:

$$E = \sum_{j=1}^{k} \sum_{x_i \in \omega_j} \left\| x_i - m_j \right\|^2$$

Among them, ω_j represents the number of clusters. x_i is the ith data of the jth cluster.

With the MATLAB, we can complete the clustering. According to the clustering result, the largest proportion of the same kind in each continent is analyzed and used as an index to measure the degree of inner closeness of "state". The rest of the calculation is similar to the previous analysis and we will not repeat because of time.

7.2 For smaller "states" (such as cities)

Some of the indicators in the fragility assessment model established above are not suitable for cities (eg, state's independence).Therefore some indicators need to be removed, and the weights for the remaining indicators need to be redefined. In addition, since the independence of cities is relatively small compared with that of a country, the neighboring cities need to be considered when considering the fragility of a single city.

Similarly, we can consider the use of Analytic Hierarchy Process to estimate the impact of neighboring cities. We can use 0-9 scale to obtain the impact of each city's weight ω_i . In addition, we use the per capita GDP as a measure of the independence of cities and define the degree of independence of cities as $I = e^{-GDP}$. The fragility of a city F' can be divided into two parts, one is its fragility F obtained through the above fragility assessment model and the other is the contribution of its neighboring cities to its fragility, which weakens when the independence of cities enhances.

$$F' = F + \sum_{i=1}^{n} I_i w_i (F_i - F)$$

8 Evaluation of Model

8.1 Strengths

- This model contains large quantities of indexes to evaluate the state's fragility. Therefore the result will be more comprehensive and more accurate.
- This model has a wide range of application. It can be applied for most countries if we have enough data. Besides, this model can also be applied to cities or continents if modified.
- In the prediction model, the core is Back Propagation. So, the model can respond correctly in spite of some noisy inputs.

8.2 Weaknesses

- Due to the lack of data, the determination of k in the cost estimation model and I in the modified model is rough. If we have enough data, we can also use AHP to calculate the value of k.
- The output of cost estimation model can vary from time to time, but the difference is acceptable.

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Appendices

Appendix A

```
%normalization of the Positive correlation index
[m,n]   = size(x);
normal = zeros(m,n);
for i = 1:m
        ma = max( x(i,:) );
        mi = min( x(i,:) );
        normal(i,:) =9*(x(i,:)-mi ).( ma-mi )+1;
        normal=ceil(normal*10)/10;
end
```

Appendix B

```
%normalization of the negative correlation index
[m,n]   = size(x);
normal = zeros(m,n);
for i = 1:m
        ma = max( x(i,:) );
        mi = min( x(i,:) );
        normal(i,:) =9*( ma-x(i,:) )./( ma-mi )+1;
        normal=ceil(normal*10)/10;
        normal=normal';
end
```

Appendix C

```
clc
clear all       %clearing memory
A=[ 1     3     3     4     5;
   1/3    1     2     2     3;
   1/3   1/2    1     1     2;
   1/4   1/2    1     1     2;
```

```
    1/5    1/3    1/2    1/2      1];%judgment  matrix
%consistency and calculation  of weight  vector
[n,n]=size(A);
[v,d]=eig(A);
r=d(1,1);
CI=(r-n)/(n-1);
RI=[0 0 0.58 0.90 1.12 1.24 1.32 1.41 1.45 1.49 1.52 1.54 1.56 1.58 1.59];
CR=CI/RI(n);
if CR<10
    CR_Result ='true';
else
    CR_Result ='fail';
end
% calculation  of weight  vector
w=v(:,1)/sum(v(:,1));
 w=w';
%Output
 disp('The  calculation  of weight  vector for judgment  matrix：');
 disp('Consistency  index：'),disp(num2str(CI));
 disp('Consistency  ratio：'),disp(num2str(CR));
 disp('Consistency  test results：'),disp(CR_Result);
 disp('Eigenvalues：'),disp(num2str(r));
 disp('weight  vector：'),disp(num2str(w));
```

Appendix D

```
%PCA
stdr=std(dataset);                  %calculating  a standard deviation  of variables
[n,m]=size(dataset);                %define  the rows and columns  of data matrix
sddata=dataset./stdr(ones(n,1),:);           %Standardizing  the raw data matrix
sddata                                        %the output  of the standardization  data matrix
[p,princ,eigenvalue,t2]=princomp(sddata);%the  first three principal  component coefficients
p3=p(:,1:3);
p3                                             %the output  of the first three principal  component  score
coefficients
sc=princ(:,1:3);
sc                                             %the output  of the first three principal  component  score
e=eigenvalue(1:3)';                       %extracting the first three eigenvalues
M=e(ones(m,1),:).^0.5;                    %the output  of the first three eigenvalues
compmat=p3.*M;                                %constructing a transformation  matrix
per=100*eigenvalue/sum(eigenvalue);        %calculating  the cumulative  contributions  of each principal
component
```

Appendix E

```
clc
clear   %clearing memory to speed up the operating process
close all;
%%Initialization
SamNum=10;                  %the size of input samples is 10
TestSamNum=10;              %the size of testing samples is 10
ForcastSamNum=2;            %the size of predicting samples is 2
HiddenUnitNum=8;            %the size of middle layer hidden nodes is 8
InDim=3;                    %3-dimensional network input
OutDim=2;                   %2-dimensional network onput
%input the related parameters
factor1=[4.7670 2.6669 2.1385 2.3742 1.9238 0.8858 -0.2651 -1.4571 -2.3309 ...
    -3.1580];
factor2=[1.9553 1.0238 0.3367 -0.4209 -0.7937 -1.5648 -1.1360 -1.6417 ...
    -2.1443 0.1653 ];
factor3=[2.1308 -0.9142 -1.5548 -0.1330 -0.8690 -0.3916 0.4028 0.7224 ...
    0.6910 0.3410 ];
%input the fragility score
fragility=[6.333 5.992 5.914 5.971 5.900 5.794 5.723 5.552 ...
    5.453 5.325 ];
%input the percentage of bad whether
disaster=[0.17 0.21 0.14 0.15 0.17 0.11 0.19 0.15 0.13 0.13 ];
p=[factor1;factor2;factor3];        %constructing the input matrix
t=[fragility;disaster];             %objective data matrix
[SamIn,minp,maxp,tn,mint,maxt]=premnmx(p,t);%initialization for
                                            %original samples
rand('state',sum(100*clock))%generating a random number on the
                            %basis of the system clock seed
NoiseVar=0.01;
Noise=NoiseVar*randn(2,SamNum);%generating noise
SamOut=tn+Noise;
TestSamIn=SamIn;
TestSamOut=SamOut;
MaxEpochs=50000;        %the maximum of training times is 50000
lr=0.035;               %the learning rate is 0.035
E0=0.65*10^(-3);        %the target error is 0.65*10^(-3)
W1=0.5*rand(HiddenUnitNum,InDim)-0.1;
B1=0.5*rand(HiddenUnitNum,1)-0.1;
W2=0.5*rand(OutDim,HiddenUnitNum)-0.1;
B2=0.5*rand(OutDim,1)-0.1;
ErrHistory=[];          %occupying memory for middle variables in advance
```

```
for i=1:MaxEpochs
        HiddenOut=logsig(W1*SamIn+repmat(B1,1,SamNum));
        NetworkOut=W2*HiddenOut+repmat(B2,1,SamNum);
        Error=SamOut-NetworkOut;
        %difference between the actualoutput  and network output
        SSE=sumsqr(Error);
        ErrHistory=[ErrHistory  SSE];
        if SSE<E0
                break
        end
        %breaking out of learning loop while the error requirement is fulfilled
        Delta2=Error;
        Delta1=W2'*Delta2.*HiddenOut.*(1-HiddenOut);
          dW2=Delta2*HiddenOut';
          dB2=Delta2*ones(SamNum,1);
          dW1=Delta1*SamIn';
          dB1=Delta1*ones(SamNum,1);
        W1=W1+lr*dW1;
        B1=B1+lr*dB1;
        W2=W2+lr*dW2;
        B2=B2+lr*dB2;
end
HiddenOut=logsig(W1*SamIn+repmat(B1,1,TestSamNum));
NetworkOut=W2*HiddenOut+repmat(B2,1,TestSamNum);
a=postmnmx(NetworkOut,mint,maxt);
x=2006:2015;
newk=a(1,:);
newh=a(2,:);
figure;
%comparison diagram of fragility  score
plot(x,newk,'r-o',x,fragility,'b--+')
legend('Network output fragility','fragility');
xlabel('year');ylabel('fragility');

pnew=[ -3.4580  -4.0871
              1.9397      0.0774
              0.0774     -0.5028];       %related data in 2016 and 2017
pnewn=tramnmx(pnew,minp,maxp);
HiddenOut=logsig(W1*pnewn+repmat(B1,1,ForcastSamNum));
anewn=W2*HiddenOut+repmat(B2,1,ForcastSamNum);
anew=postmnmx(anewn,mint,maxt)  %output the predicted data
```

Appendix E

```
clear
clc
a = 0.95;
cost = [500;471;1348;475;369;1107;213;687;541;864;779;418];
%Each refuge's setting costs;Unit:thousand dollars.
refugee = [4.3;5.1;13.5;3.9;2.5;5.4;1.2;4.8;3.5;7.7;10.4;6.5];
%The nurber of refugees that can be relieved by each refuge;Unit:thousand.
N = 54.3;
num = 12;
sol_new = ones(1,num);                 % Founding initial solution
N_current = inf;N_best = inf;
% N_current:the objective function value of the current solution;
% N_new:the objective function value of the new solution;
% N_best:the objective function value of the best solution;
sol_current = sol_new; sol_best = sol_new;
t0=97; tf=3; t=t0;
p=0;
while t>=tf
    for r=1:100
        %random disturbance
        tmp=ceil(rand.*num);
        sol_new(1,tmp)=~sol_new(1,tmp);

        %Check whether the constraint is satisfied
        while 1
            q=(sol_new*refugee >= N);
            if ~q
                p=~p;     %Reciprocating and reversing the first one
                tmp=find(sol_new==0);
                if p
                    sol_new(1,tmp)=1;
                else
                    sol_new(1,tmp(end))=1;
                end
            else
                break
            end
        end
        % Culculate the whole nurber of refugees that can be relieved in this solution
        N_new=sol_new*cost;
        if N_new<N_current
```

```
            N_current=N_new;
            sol_current=sol_new;
            if N_new<N_best
                % Saving the best solution in the cooling process
                N_best=N_new;
                sol_best=sol_new;
            end
        else
            if rand<exp(-(N_new-N_current)./t)
                N_current=N_new;
                sol_current=sol_new;
            else
                sol_new=sol_current;
            end
        end
    end
    t=t.*a;
End
disp('The best decision is：')
sol_best
disp('The cost of this decision is：')
val=N_best;
disp(val)
disp('The number of refugees being helped :')
disp(sol_best * refugee)
```

Appendix F

```
%N:The number of categories the data is divided into
%u:Cluster centers of each categories
function [u re]=KMeans(data,N)
    [m n]=size(data);      %define the rows and columns of data matrix
    ma=zeros(n);           %the maximum of each dimensional
    mi=zeros(n);           %the minimum of each dimensional
    u=zeros(N,n);          %Randomly initialized until getting the center of each class
    for i=1:n
       ma(i)=max(data(:,i));
       mi(i)=min(data(:,i));
       for j=1:N
            u(j,i)=ma(i)+(mi(i)-ma(i))*rand();
       end
    end
```

```
    while 1
        pre_u=u;
        for i=1:N
            tmp{i}=[];
            for j=1:m
                tmp{i}=[tmp{i};data(j,:)-u(i,:)];
            end
        end

        quan=zeros(m,N);
        for i=1:m
            c=[];
            for j=1:N
                c=[c norm(tmp{j}(i,:))];
            end
            [junk index]=min(c);
            quan(i,index)=norm(tmp{index}(i,:));
        end

        for i=1:N
           for j=1:n
                u(i,j)=sum(quan(:,i).*data(:,j))/sum(quan(:,i));
           end
        end

        if norm(pre_u-u)<0.1    %Continuously  iterating  until
                                  %the position  is no longer  changed
            break;
        end
    end

    re=[];
    for i=1:m
        tmp=[];
        for j=1:N
            tmp=[tmp  norm(data(i,:)-u(j,:))];
        end
        [junk  index]=min(tmp);
        re=[re;data(i,:)  index];
    end
end
```

Appendix G Data

country	*PM2.5*	*CE*	*GDP*	*AGGR*	*CEPG*	*STJA*	*EI*
Sudan	100	15779.1	812.04	3.47	0.11	309.8	9.5
Democratic Republic of the Congo	98.93	3252.63	237.57	7.08	8.44	18.3	8.8
Côte d'Ivoire	99.92	6446.59	946.98	-4.39	0.12	218.8	7.9
Iraq	100	111447.5	2151.55	6.4	0.29	606.6	8.4
Chad	100	517.05	708.21	13.55	0.02	6.3	9.2
Afghanistan	99.72	8470.77	366.32	8.43	0.19	29.3	8.7
United States	64.42	5408869	43961.17	2.53	0.36	398121.9	5.4
China	99.5	8256969	36210.36	10.63	0.67	305827	9
Australia	4.89	368170.5	39300.97	2.02	0.43	40078.9	4.2
United Kingdom	77.73	492192.1	7814.8	1.54	0.22	91788.5	4.5
Turkey	99.74	298002.4	30788.54	9.16	0.25	26172.8	7.8
Italy	99.98	405361.2	37204.08	1.71	0.2	57362.5	4.5
Germany	99.95	750697.3	3410.43	4.08	0.23	95135.1	4.7
Thailand	89.48	298141.8	34758.13	7.51	0.34	6966.2	7.5
Singapore	100	13479.89	1564.07	15.24	3.76	9617	3.1
Indonesia	71.16	436981.7	5587.25	6.22	0.22	1281.3	7.9
Brazil	44.1	419754.2	7076.3	7.53	0.15	40530.5	8.8
Argentina	38.05	179000.9	10075.11	9.45		7420	5.8
Poland	100	317081.8	6354.12	3.7	0.4	23706.2	4.8
Malaysia	76.98	224589.1	812.04	7.43	0.39	11280.7	7

country	SED	RP	DP	TL	PS	HR	SL	IPI	SPI
Sudan	1656163	178308	9.9	8	9	9.4	8.8	3.4	3.794
Democratic Republic of the Congo	2797329	166336	8.5	9.3	8.4	9.1	9	1.6	2.824
Côte d'Ivoire	999932	24221	8.4	8.2	8.3	8.3	9	2.2	2.956
Iraq	1966640	34655	8.1	7.9	7.3	8.9	8.9	3	4.162
Chad	424815	347939	9.1	6.1	9.2	8.8	9	2.6	2.853
Afghanistan	2032719	6434	8.3	8.6	9	9.5	9.8	3	4.147
United States	24192790	264574	3.1	1.1	2.5	3.7	2.5	2	2.044
China	78798730	300986	8.8	5.9	7	9	8.3	2.2	2.338

Australia	1533093	21805	3.5	1.2	1.8	2	1.5	1.4	1.368
United Kingdom	4805310	238150	3.2	1.8	2.3	2.3	1.6	1.6	1.75
Turkey	5890584	10032	6.3	4.8	5.4	5.5	6	2.4	2.632
Italy	2917647	56397	4	2.8	3.1	3	4.5	1.2	1.971
Germany	6106595	594269	3.3	2.6	1.7	2.3	2.1	1.2	1.441
Thailand	4054280	96675	6.7	4.7	5.4	7	8	2.4	2.882
Singapore		7	2.8	2.5	1.7	4.4	4.2	1.2	1.647
Indonesia	16656850	811	7.2	7.3	6.7	6.5	6.9	1.6	2.132
Brazil	22215050	4357	6.3	4.8	6	5.4	6.2	1	2.897
Argentina	3407939	3276	4.6	3.8	3.7	3.8	3.6	1.4	2.221
Poland	2027552	15555	4.7	5.9	3.7	3.8	4.5	1.6	1.559
Malaysia	2453474	81516	6.3	3.9	5	6.8	5.9	1.2	2.059