Flood Loss Prediction of Coastal City Based on GM-ANN

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***Abstract*—Flood loss prediction is very important in China. In this paper, flood factors of coastal city, such as geological sedimentation rate, rise in sea level height, precipitation, urban drainage pipe length, annual GDP and population throughout the year will be considered to predict flood loss. Firstly, AHP will be used to determine the weight of flood factors. Considering the characteristics of different factors, GM is applied to get predictive values of flood factors. Then predictive values and weights are applied to ANN method to obtain flood loss of coastal city. Finally, Shenzhen is regarded as an example to verify the feasibility of this methods GM, DGM and ANN methods compared.**

Keywords*—*flood loss; prediction; flood factors; AHP; GM; ANN

I. INTRODUCTION

According to the statistics, China is one of the countries which affected by the flood natural disaster to the deepest extent. Recent years, the healthy development of the economy has been influenced by global warming and serious typhoons in China's coastal cities [1]. At present, there are lots of flood risk assessment methods [2,3,4], but the specific flood loss predictive method is not common. Therefore, in this paper, after mastering raw flood disasters data of coastal cities, city flood loss predictive model of coastal cities is established to accurately grasp the basic characteristics of flood loss phenomenon of coastal cities and perfect the urban flood loss prediction system.

II. FLOOD LOSS PREDICTIVE METHOD BASED on FLOOD FACTOR

Usually, an urban flood disaster system is composed of hazard-pregnant body (C_1), hazard-caused body (C_2) and hazard-affected body (C_3), the various factors interacted lead to the flood risk[5]. Hazard-pregnant body is composed of geological subsidence, sea level and other factors. Hazard-caused body may include rainfall, urban drainage facilities and other factors. Hazard-affected body is composed of all kinds of resources in human society. Combining with the characteristics of coastal cities in this paper, urban geological sedimentation height (P_1) and sea level rise height (P_2) are regarded as hazard-pregnant body. Average annual precipitation (P_3) and urban drainage pipe length (P_4) are regarded as hazard-caused body. Resident population (P_5) and city GDP (P_6) are regarded as hazard-affected body [6,7].

A. Determine flood factor weight of coastal cities

The AHP method is widely used to determine weights. The figure of determining flood factors weights used in AHP is shown in Fig1.

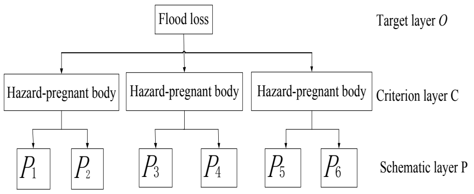

Fig. 1. Flood factor hierarchy analysis figure

i. According to the theory of AHP, comparison discriminant matrix of the layer to last layer was constructed. According to the expert opinion scale method, the comparison discriminant matrix shows as follows.

$$O=\begin{pmatrix} 1 & 1/5 & 3 \\ 5 & 1 & 7 \\ 1/3 & 1/7 & 1 \end{pmatrix} \qquad C_1=\begin{pmatrix} 1 & 1/7 \\ 7 & 1 \end{pmatrix}$$

$$C_2=\begin{pmatrix} 1 & 1/4 \\ 4 & 1 \end{pmatrix} \qquad C_3=\begin{pmatrix} 1 & 1/6 \\ 6 & 1 \end{pmatrix}$$

ii. After the above model, software called yaahp was used to solve the model. Then flood factor weight is shown in TABLE I.

TABLE I. FLOOD FACTOR WEIGHT BASED ON AHP

factor	P_1	P_2	P_3	P_4	P_5	P_6
weight	0.0116	0.1648	0.1461	0.5845	0.0235	0.0694

iii. Finally, the consistency ratios of inspection criterion layer are less than 0.1 after test. The result comforts to test standard of AHP which stated feasibility of evaluation model's [8].

After the above assessment, the cumulative contribution rates of P_2-P_6 have achieved 99%. Therefore, to simplify method, the P_1 can be abandoned completely in the next predictive method. The rest flood factors are normalized to apply to ANN method as input weight.

B. Flood factor prediction based on GM(1,*N*)

GM(1,*N*) shows a one-order grey model including n variables.

1) Predictive method of flood factor P_4

Considering the city drainage pipe length is limited to sea level height(P_2), average annual precipitation (P_3), resident population(P_5) and city GDP(P_6). The city drainage pipe length P_4 is regarded as system characteristics sequence data, P_2、P_3、P_5、P_6 are regarded as sequence data system related factors. The grey system prediction would be showed as follows based on above.

Assuming the raw sequence of GM(1,N) is $X_i^{(0)}=\{X_i^{(0)}(1),\ X_i^{(0)}(2),\cdots,\ X_i^{(0)}(n)\}$, $X_i^{(1)}$ is corresponding accumulative sequence, $Z_i^{(1)}$ is corresponding average sequence. Therefore, an albino differential equation has been got as follows.

$$\frac{dx_1^{(1)}}{dt}+ax_1^{(1)}(t)=\sum_{i=2}^{N}b_ix_i^{(1)}(t) \tag{1}$$

Parameters a, b_i can be calculated by least square method, then discrete time response function of grey prediction is as follows.

$$x_1^{(1)}(k+1)=[x_1^{(0)}(1)-\frac{1}{a}\sum_{i=2}^{n}b_{i-1}x_i^{(1)}(k+1)]e^{-ak}+\frac{1}{a}\sum_{i=2}^{n}b_{i-1}x_i^{(1)}(k+1) \tag{2}$$

$x^{(1)}(k+1)$ calculated above is predictive value of city drainage pipe length. Then predictive value was reduced as follows.

$$\hat{x}_1^{(0)}(k+1)=\hat{x}_1^{(1)}(k+1)-\hat{x}_1^{(1)}(k) \tag{3}$$

2) Predictive method of flood factor P_2 and P_3

In grey predictive method GM(1,N), when N=1, it shows a one-order equation grey model one variable included. Considering the factors affecting the complexity of two factors sea level rise height(P_2) and average annual rainfall(P_3), let this as a grey box, GM(1,1)model was used to predict the two flood factors.

An albino differential equation has been get by simplifying GM(1,N) model as follows.

$$\frac{dX^{(1)}}{dt}+aX^{(1)}=u \tag{4}$$

Then the discrete time response function of grey prediction is as follows.

$$X^{(1)}(t+1)=\left(X^{(0)}(1)-\frac{u}{a}\right)e^{-at}+\frac{u}{a} \tag{5}$$

$x^{(1)}(k+1)$ get above is predictive value of the two flood factors. Then predictive value was reduced as follows.

$$\hat{X}^{(0)}(t+1)=\hat{X}^{(\ )}(t+1)-\hat{X}^{(\ )}(t) \tag{6}$$

To ensure that predictive values according with actual, "same dimension grey available predict" method was used, which is that a new predictive value added to the known model, at the same time, the old raw were get rid of to ensure same length of sequence until that predictive year[9].

C. Flood loss prediction based on GM-ANN

In the moving forward of the ANN, the input signal is processed step by step during input layer through the hidden layer until output layer. Each neurons state of this layer only affects neurons state of next layer. If the output result is not expected output, the process will enter into the back propagation. In this process, the network weights and thresholds would be adjusted according to the predictive error. Therefore, the predictive value based on ANN would expect the looming output [10,11,12,13].

The flood loss prediction of coastal city is shown as topology figure Fig2. As far as possible in order to reduce the complexity of this model, combining the stability development trend of the coastal city, resident population (P_5) and city GDP(P_6) merged a new flood factor called per GDP(P_7)as an input in ANN. In other words, sea level rise height (P_2), average annual rainfall (P3), city drainage pipe length (P_4) and per GDP(P_7)are all regarded as ANN's inputs, and urban flood loss is the only output. Therefore, flood predictive ANN model's four inputs and the only output included are already built.

According to ANN's empirical analysis, the hidden layer node number n_1=2n+1(n are input numbers) was adopted as preliminary reference in hidden layer. Hidden node numbers are changing during the process of network training, then different hidden layer node numbers' training error were compared to ensure the best hidden layer node numbers.

To initialize the connection weights W_{ij} and W_{jk} among input layer, hidden layer and output disasters. In this paper, Shenzhen as an example, layer neurons, threshold value a_k in hidden layer and threshold value b_k in output layer. In this example, the learning rate experience value is 0.01-0.7, the incentive function of neurons is sigmoid function as follows.

$$f(x)=\frac{1}{1+e^{-x}} \tag{7}$$

According to the input vector X, connection weight W_{ij} between input layer and hidden layer, threshold value a_k in hidden layer, computing output H_j of hidden layer.

$$H_j=f(\sum_{i=1}^{n}W_{ij}X_i-a_j),\ \ j=1,2,\ldots,n. \tag{8}$$

According to H of hidden layer, connection weight W_{ij} and threshold value b, predictive value Y of ANN was computed.

$$Y_k=\sum_{j=1}^{l}H_jW_{jk}-b_k \tag{9}$$

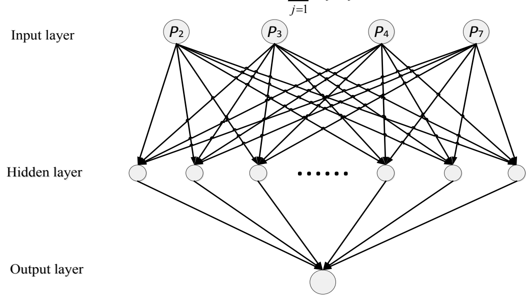

Fig. 2. ANN's topology figure on flood loss

III. EXAMPLE of FLOOD LOSS PREDICTION

Shenzhen is near the sea and is often attacked by typhoon since recent few years. Its loss is greatly influenced by the flood. In view of this phenomenon, GM-ANN method system was constructed to predict the flood loss in the future in Shenzhen.

From statistical yearbook in Shenzhen, China sea announcement, meteorological bureau of Shenzhen municipality, flood loss in Shenzhen and flood factor data in 2007-2014 were shown in TABLE II

TABLE II. FLOOD FACTOR STATISTICS IN SHENZHEN

Year	Sea level rise height (mm)	Average annual rainfall (mm)	Urban drainage pipe length (km)	Per GDP (10 thousand/person)	Flooding loss (10 thousand)
2007	54	1581.5	6808.2	10.511	5432.5
2008	75	2710.0	9984.2	11.412	6272.7
2009	64	1611.0	10152	11.334	7359.8
2010	74	1634.0	11844.6	12.638	8756.2
2011	93	1269.7	12144.1	15.049	11318.7
2012	82	1554.8	12212.2	16.792	23272.5
2013	87	2203.6	12418.8	16.125	27370.2
2014	96	1933.3	12312.7	17.065	25428.2

a. ----------------- statistic yearbook in Shenzhen

TABLE III. PREDICTION OF FLOOD FACTOR IN SHENZHEN

Year	Sea level rise height (mm)	Average annual rainfall (mm)	Urban drainage pipe length (km)	Per GDP (10 thousand/person)
2020	112.80	1927.33	15265.21	27.0392
2022	117.30	2129.10	18957.58	30.4270
2024	121.94	2351.99	19857.23	35.8741
2028	123.09	2598.21	20267.45	38.2309

A. training simulation of ANN

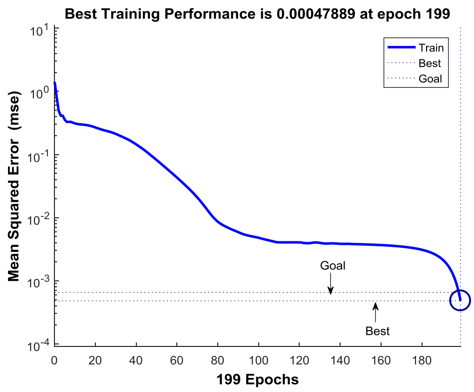

Fig. 3. Training vector epoch of ANN

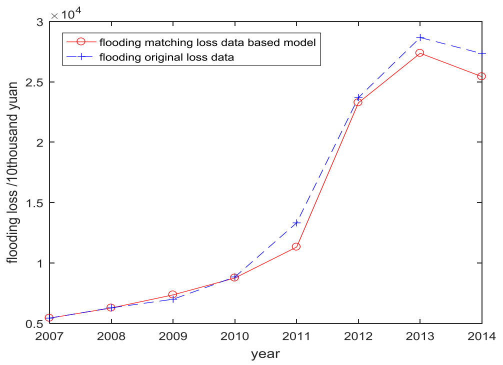

Fig. 4. Flood loss simulation compared figure

The 80% raw data of related factors in 2007-2014 were regarded as training vector, the rest data were regarded as test vector [14] . Matlab was used to train the raw data until near the target at epoch 199. Additional, the raw data and data of simulation contrast figure shows that the flood predictive results from ANN model are very close to real values so that it is possible as the flood predictive model.

B. Flood loss factor prediction

GM (1,N) was used to predict city drainage pipe length(P_4) while GM (1, 1) was used to predict flood factor P_2 and P_3. To flood factor P_7, its predictive value could be get according to statistical yearbook's development trend. Compared the results between predictive data and raw data, it is easily find that the flood factor predictive mean error is less than 0.1 which makes the precision of prediction to first class[15]. Therefore, this kind of predictive method was adopted to flood prediction of coastal city. Flood factor predictive result was shown in TABLE III.

C. Flood loss prediction of Shenzhen City

In TABLE IV, compared to the GM predictive method, the GM-ANN model significantly improved in error. The simulation function Y = sim (net, P_test) was used to normalize in MATLAB [16], the flood loss predictive value has been calculated in TABLE V.

TABLE IV. .COMPARDE RESULTS BETWEEN GM AND AHP-GM-ANN MODEL

Year	Flood raw data	GM(1,1)	DGM(1,1)	GM-ANN
2007	5432.5	5432.5	5432.5	5432.5
2008	6272.7	6884.1	7182.0	6285.6
2009	7359.8	8814.9	9148.4	6996.4
2010	8756.2	11287.3	10653.3	8842.9
2011	11318.7	14453.0	13843.8	13321.2
2012	23272.5	18506.8	19907.9	23697.8
2013	27370.2	23697.4	23084.8	28671.4
2014	25428.2	30344.0	28679.1	27340.2
Predictive average error		17.42%	15.71%	4.74%

TABLE V. FLOOD LOSS PREDICTION IN SHENZHEN

Year	2020	2022	2024	2028
Flood loss	25743	27076	28521	30945

IV. CONCLUSION

In this paper, AHP-GM-ANN model was constructed to predict flood loss of coastal city. AHP is used to determine the weight, GM(1,4) and GM(1,1) are adopted to predict flood factors of different characteristics. What's more, ANN model is combined to predict flood loss in Shenzhen. From these predictive results, compared with the simple GM model, AHP-GM-ANN model would significantly reduce the predictive error while reliable results get.

AHP-GM-ANN model not only solved nonlinear variable relationship problems in predictive method, but also improved the accuracy of the system of quantitative prediction methods. More importantly, to each step establishment in model, there is a corresponding error analysis which enhanced the correctness and scientific security of the predictive method system.

REFERENCES

[1] Jiang Zou ,Jianzhong Zhou and Chao Zhou, " The flood disaster analysis based on the theory of variable fuzzy sets", Journal of agricultural engineering, pp.51-54,2012.

[2] Qiang Gao. "Economic damage forecast for storm surge in Shandong province" , Marine economic journal, vol. 29 pp .110-117,2015.

[3] Qin Chen, " Fire damage prediction based on markov grey residual GM (1, 1) model", Journal of Nanchang university, vol. 35.pp.84-87,2015.

[4] Xiong Kuang, " The study of flood loss assessment based on the spatial information grid and BP neural network", Jiangxi university of technology,pp.123-125,2015.

[5] Haibo Hu and Yanli Zhang, "Storm disaster personnel loss risk assessment models", Journal of disaster science, vol.29,pp. 30-36.,2015 .

[6] Xiaoqing Luan, "An introduction to mathematical modeling". Beijing: higher education press, 2014 .

[7] Fan Wu, "Predictive research of Neural network", East China university of science and technology, pp. 29 -34,2015 .

[8] Sifeng Liu, Yaoguo Dang and Zhi-geng Fang, "The grey system theory and application" ,Beijing: science press, 2015.

[9] Wanmei Tang, "The new prediction model based on grey support vector machine", Journal of systems engineering, vol.21,pp. 410- 413,2015 .

[10] Jing Wang, "The precision and error research of grey model", Journal of Knowledge and practice of mathematics, vol.26,pp.68-70,2016.

[11] Jingling Yuan, "Gray neural network research and development", journal of wuhan university of technology, vol 35,pp. 91-93,2015.

[12] Jinchuan Cui, "Flood loss relative evaluation and forecast method research", Journal of systems engineering, vol. 17,pp.337-342,2015 .

[13] Zhong Yun, "City's direct loss assessment and prediction of flood disasters", Journal of water conservancy, pp. 64-68, 2014 .

[14] Gongzhou Wang, "Comprehensive evaluation based on analytic hierarchy ", Water safety in Anhui province the south-north water diversion and water conservancy science and technology, vol.12 ,pp.38-42 ,2013.

[15] Xiuhong Yan, "Improved grey neural network combination forecast method and application research ", Master thesis, jiangxi university of science and technolog,pp.23-26,2016.

[16] Xin Wen, "MATLAB neural network application design", Beijing: science press, 2015.