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Smart Growth Evaluation System based on Fuzzy Theory and Neural Network

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***Abstract* – This paper puts forward a method of smart growth based on fuzzy theory and neural network. First of all, we have collected a large number of references and expert advice to make a qualitative analysis of the factors that may affect the development of smart city, and get 21 evaluation indicators. Dynamic particle swarm algorithm and fuzzy theory are used to extract and optimize the possible indicators, finally we get twelve of the most sensitive evaluating indicators. The fuzzy transformation would be utilized to complete the quantitative analysis of each evaluating indicator by giving each indicator a corresponding weight. In the course of actual evaluation, we adjust the weight slightly by training BP neural network and output the final evaluation score.**

***Keywords* – Smart Growth; Evaluation System; Fuzzy Theory; Neural Network.**

I. INTRODUCTION

The traditional evaluation method is based on linear model [1, 2]. According to the score of each indicator, it adds up the weight of each indicator to get the final scores. This kind of method has some shortcomings [3, 4, 5]. It needs the evaluation personnel to have an accurate evaluation for each indicator, which is a strict requirement. Usually only experts in this area can finish the work. Generally, they can only make qualitative judgments on the evaluation of each indicator, and most of them lack stable theoretical support.

This paper puts forward a method of smart growth based on fuzzy theory and neural network. At first, the fuzzy transformation is used to convert the fuzzy evaluation of the hierarchical indicator into the overall fuzzy evaluation. Training samples were obtained by collecting a large number of references and expert opinions. Then, we use BP neural network to adjust the weight. After the stability of the system, the fuzzy evaluation which is given by the general evaluation personnel can be directly used as input to calculate the expert evaluation results. The model structure of the system is shown in figure 1:

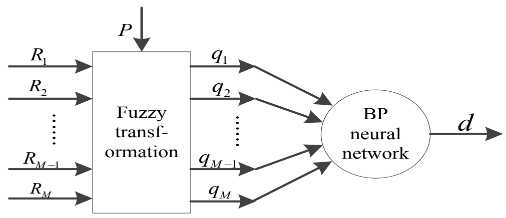

Fig. 1. Structure of system model

In this system, according to the corresponding fuzzy evaluation relation R_i and weight vector P of each indicator, we obtained the overall fuzzy evaluation relationship $Q=[q_1,q_2,\cdots q_N]$ through fuzzy transformation. The BP network uses Q as an input value and calculates the final actual score value d.

II. EVALUATION OF FEATURE EXTRACTION AND QUANTIFICATION

In order to obtain the evaluation indicator of smart growth, we have collected a large amount of literature and expert advices. Based on the evidences, we make a qualitative analysis of the indicators about smart growth, and get 21 possible evaluation indicators related to smart growth. As shown in Table 1:

Table 1. Possible evaluation indicators

X_1	X_2	X_3	X_4	X_5	X_6	X_7
Urban employment rate	per capita income	Per capita GDP	Proportion of agricultural land	City GDP	Urban green coverage rate	Total urban consumption
X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
Agricultural land per capita	Per capita park green space	City average noise level	City average noise level	Proportion of urban population	Per capita road length	Per capita bus route length
X_{15}	X_{16}	X_{17}	X_{18}	X_{19}	X_{20}	X_{21}
Urban population growth rate	Urban per capita Road area	Medical beds per capita	Per capita number of schools	Number of books per capita	Per capita number of cars	Urban population density

In order to facilitate the study, we use fuzzy logic to quantify the evaluation indicator of the table 1. The quantitative results are used to show the impact of each evaluation indicator on Smart Growth, using a set of vector [4, 3, 2, 1] to represent the level of each indicator: very high (4), relatively high (3), fair (2), low (1).

After collecting a large number of references and expert advices, we use discrete particle swarm optimization to extract and optimize the indications. In order to guarantee the calculation speed, and not fall into local optimum, the size of each group of data is set to 25. The Control parameters are: α=0.3, β=0.7, $c_1=0.4$, $c_2=0.6$. The Maximum number of iterations of particle swarm is 30. Feature selection optimization results are shown in figure 2.

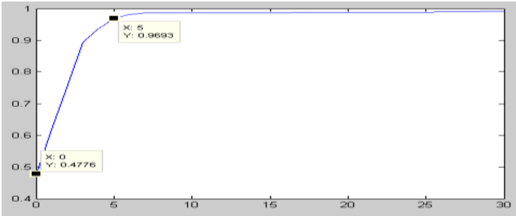

Fig. 2. DPSO feature selection optimization results

The abscissa represents the number of iterations and the ordinate represents the fitness value. What can be seen from the above table is that this group find the optimal solution on the fifth step. The selected feature data is X1, which represents the urban employment rate. The fitness is 0.9683.

Other training samples and features are extracted in the same way. Partial particle swarm selection results as shown in Table 2.

Table 2. Feature extraction of partial particle swarm

Data	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}
Group1	1	0	1	1	0	1	0	0	0	0	0	1	1	1	0	1	1	1	0	0	1
Group2	1	0	1	1	0	0	0	0	0	0	1	1	1	1	0	1	1	1	0	0	0
Group3	1	1	1	0	0	1	0	0	0	0	1	1	1	1	0	1	1	1	0	0	0
Group4	1	0	0	1	1	1	0	0	0	0	1	1	1	1	0	0	1	1	0	0	1
Group5	0	0	1		0	1	0	0	0	0	1	1	1	1	0	0	1	1	0	0	0
Group6	1	0	1	1	0	1	1	0	0	0	1	0	1	1	0	1	1	1	0	0	0
Group7	1	0	1	1	0	1	0	1	0	0	1	1	0	1	0	1	1	1	0	1	1
Group8	1	0	1	1	0	1	0	0	1	0	1	1	1	0	0	0	1	1	1	0	0
Group9	1	0	1	1	0	1	0	0	0	1	1	1	1	1	0	1	0	1	0	0	0
Group10	1	0	1	1	0	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0

Note: 1 represents be extracted; 0 represents not be extracted

After the completion of all indicators, we summary the extraction result as the following:

Table 3. The summary of extraction results

Indicator number	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Extraction times	469	10	445	463	15	435	15
Indicator number	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
Extraction times	11	11	11	486	478	467	464
Indicator number	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}	X_{20}	X_{21}
Extraction times	17	11	466	489	14	18	17

Within the allowable error range, from the table above, we can see that the characteristics indicator of smart growth, such as: $X_1, X_2, \cdots, X_{21}$, and what they represent is shown in Table 1.

After feature extraction and optimization, we renumbered the 12 indicators that we obtained. $U_i(1,2,\cdots 12)$ represents i th characteristic indicator. In order to determine the weight of each indicator for smart evaluation, we need to use the weight coefficient of the quantitative table for the quantitative analysis of each indicator, as shown in the following tables.

Table 4. Weight coefficient table

Comparison of indicator u_i and indicator u_j	A_{ij} Value
u_j is as important as u_i .	1
u_i is slightly important than u_j	3
u_i is obviously important than u_j	5
u_i is fundamental important than u_j	7
u_i is absolutely important than u_j	9

Every influence on child nodes caused by the father notes reflects for the weight vector, we take "the proportion of fuzzy similar matrix method" to calculate the weight vector. We organized experts to compare all of the indicators two by two according to table one, then we got comparison matrices $A=[a_{ij}]_{N\times M}$, a_{ij} refers to indicator u_i and u_j 's quantitative comparative relationship, and set $a_{ji}=1/a_{ij}$. Then calculate every single line's element's product's N-th root from matrix A to form vector $P=[p_1,p_2,\cdots p_N]$, then normalized and got the weight function P . Every evaluating indicator's weight function is allocated as the following table 5.

Table 5. Indicator weight distribution of Smart growth

First-grade Indicator			second-grade Indicator		
Name	Weight	Identific -ation	Name	Weight	Identific -ation
			Urban employment rate	0.37	U_{11}
			Per capita housing area	0.26	U_{12}
economic	0.27	U_1	Per capita GDP	0.16	U_{13}
			Per capita disposable income	0.21	U_{14}
			Proportion of agricultural land	0.17	U_{21}
ecological	0.32	U_2	Urban green coverage rate	0.47	U_{22}
			Annual air quality rate	0.36	U_{23}
			Proportion of urban population	0.13	U_{31}
			Urban per capita road length	0.18	U_{32}
equitable	0.41	U_3	Vehicle per capita	0.11	U_{33}
			Medical beds per capita	0.31	U_{34}
			School per capita	0.27	U_{35}

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III. Fuzzy Transformation Processing

In the fuzzy set theory, the value of X in the closed interval [0, 1] that used to describe the membership of the set A. The fuzzy set of A, which is very suitable for simulating human cognition and perception. At the same time, the fuzzy relation is used to describe the degree of association between two sets of elements. If $A=[a_1,a_2,\cdots a_m]$ is the fuzzy set on the domain V, $R=[r_{ij}]_{m\times n}$ is the fuzzy relation on the domain $V\times U$, $B=A\circ$ is defined as fuzzy transformation. The operator '$\circ$' is defined as follows：

$$b_k=\bigvee_{i=1}^{m}(a_k\wedge r_{ik}),k=1,\cdots,n$$

In the equation, '$\vee$'means the maximum value, '$\wedge$' indicates the minimum value. By using the transformation, the fuzzy evaluation relation of the hierarchical indicator can be transformed into the fuzzy evaluation.

In previous set indicator system, assume one main joint contains M sub-joints, then sub-joints matched M appraisal indicator formed indicator domain $U=\{u_k\}$; elected N uncertain appraisal class formed domain $V=\{v_k\}$; sub-joints matched weight vectors are $p=[p_1,p_2,...,p_M]$.

Organize assessors to make uncertain appraisal for M indicators then for indicator statistic appraisal class distribution. Assume indicator term u_i are appraised as v_j 's people occupies ratio r_{ij} in all appraisal people. $R=[r_{ij}]_{M\times N}$ forms domain $U\times V$ uncertain relationship. Use weight vector P to R undergoing uncertain transition to get main joints matching indicator's uncertain relationship $Q=P\circ$ in domain V.

Let Q normalizing to get main joint uncertain appraisal result Q and regard as one leaf joint later. Repeat previous steps to solve upper class indicator appraisal one by one and get whole uncertain appraisal.

IV. BP Neural Network Training

BP neural network is a kind of unidirectional propagation multilayer feed forward neural network. In addition to the input layer and the output layer, it also has one or a plurality of hidden layers. Each layer of neurons only receives the input from the previous layer, and the nodes in the same layer are not connected with each other. Input data $X=(x_1,x_2,\cdots,x_n)$ from the input layer through the hidden layer node to the output layer, get the output data $Y=(y_1,y_2,\cdots,y_m)$.

Neural network is used to realize the automatic acquisition of knowledge. The network training samples (X_K,Y_K) are provided by the industry experts and the reference documents' Learning examples and the corresponding expected solutions. The adaptive learning algorithm is used to modify the network structure and the weight value distribution of each sensor, and make the expected output value of the network approximates the actual output value. When the network stabled, the knowledge and experience of industry experts is reflected to the structure and weight value distribution in the network.

To layered uncertain transition formed the whole uncertain marking Q, we have designed a N input single output BP web to make final certain marking to clear increasing.

This web contains one hidden layer which has joints. Transition function is double curve tangent function. Then organize experts marking for L targets with single indicator in either uncertain or the whole. Let single indicator uncertain appraisal undergo uncertain transition to get L group whole uncertain appraisal Q_k^*, $k=1,2,\cdots,L$; Matched whole marking is d_k^*, $k=1,2,\cdots,L$. (Q_k^*,d_k^*) forms BP web study sample.

Assume input layer to hidden layer's link weight matrix $[W_{ij}^1]_{N\times M}$, hidden layer to output layer's link weight matrix $[W_i^2]_{N\times 1}$. For, W_{ij}^1 represents input joint i to hidden layer joint j 's link weight and W_i^2 represents hidden layer i to output joint's link weight. Therefore, hidden layer joint i matched input is $I_i=\sum_{k=1}^{N}W_{ki}^1 q_k^*$, output is $O_i=f(I_i)$. Employ error reverse spread algorithm practice grid, steps are as below:

(1) Set all weight values as initial random value between 0-1 and let study time equal to 1 and undergo cycled study.

(2) Let $t=t+1$: if $t>L$ then let $t=1$ and undergo cycled study.

(3) Take t group sample to calculate grid error between acute output and expectation $\Delta t=(d-d_t^*)^2$; if all samples errors meet ε then the practice finishes. ε is the user defined error value.

(4) Modify hidden layer to output layer's link weight value and input to hidden layer's link weight value: let $W_i^2=W_i^2+\Delta W_i^2$, $W_{ij}^1=W_{ij}^1+\Delta W_{ij}^1$; in equation $\Delta W_i=\eta\circ\quad\circ\quad$; $\Delta W_i^2=\Delta W_i\circ$, $\Delta W_{ij}^1=\eta\circ\quad\circ\quad\circ$, η is study rate.

(5) Skip to step 2.

V. Application

A. Smart Growth Indicators

We have defined this indicators in the second part-Evaluation of feature extraction and quantification. By collecting a large number of references and expert advice, we can make a qualitative analysis of the factors that may affect the smart growth. We use fuzzy theory and dynamic particle swarm optimization algorithm to extract the possible influence factors. Finally, we get 12 indicators to measure the city's smart growth. The smart growth evaluation system is shown in the figure 3.

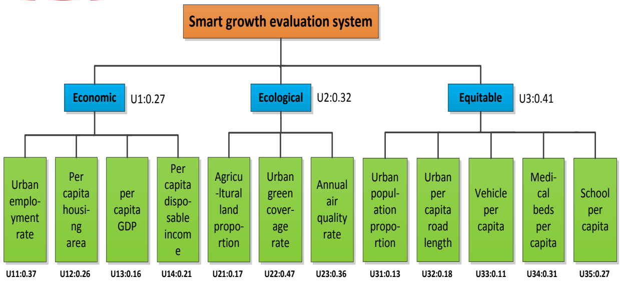

Fig. 3. Smart growth evaluation system diagram

B. The Success of the Current Urban Growth Plan

After the establishment of the evaluation model, according to the requirements of the subject, we need to choose two cities from different continents to use the established model for evaluation and analysis. Considering the convenience of data collection, while ensuring that the choice of the two cities to be representative, we finally choose Vaughan, Canada and Lobito, Angola for evaluation analysis. Statistics for the two cities are as follows.

Table 6. Statistics of urban data

City	Employment rate/%	Per capita housing area/m^3	Per capita GDP/dollar	Per capita disposable income/year/thousand
Vaughan	60.50%	38	50340	0.32
Lobito	47.39%	18	5256	0.0242

City	Agricultural land Proportion /%	Green coverage rate/%	Air quality excellent days / year	Proportion of urban residents/%
Vaughan	34.83%	35.72%	105	77%
Lobito	64.72%	21.59%	45	47%

City	Per capita road length/m	Number of cars/ per1,000	Medical beds/ per1,000	School number/ per1,000
Vaughan	2.37	668	7.5	0.365
Lobito	1.46	85	1.3	0.036

First, we take the city of Vaughan as an example to illustrate the use of the evaluation method. We set the second-level indicator in table 6, and we set five evaluation levels for each indicator, as follows:

$90 \le v_1 \le 100$: Excellent; $80 \le v_2 < 90$: Good;

$70 \le v_3 < 80$: Medium;

$60 \le v_4 < 70$: Worse; $50 \le v_5 < 60$: Worst

The weight vectors corresponding to each indicator have been obtained in the above, so that the second-level indicator of economic is as follows:

$$p_1 = [0.37, 0.26, 0.16, 0.21]$$

Ecological correspondence:

$$p_2 = [0.17, 0.47, 0.36]$$

Equitable correspondence:

$$p_3 = [0.13, 0.18, 0.11, 0.31, 0.21]$$

The second-level indicator correspondence:

$$p = [0.27, 0.32, 0.41]$$

Then we construct a BP network and use the sample to train the network. Moreover we take $\varepsilon = 0.0025$, $\eta = 0.1$ in the algorithm. Once the training is over, the evaluation system has been established successfully.

We organize 12 evaluation personnel to take fuzzy evaluation into consideration for Vaughan City. The results are shown in the table 7.

Table 7. Score results of Vaughan

Number	U_{11}	U_{12}	U_{13}	U_{14}	U_{21}	U_{22}	U_{23}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}
1	96	81	88	67	87	93	88	78	78	80	74	82
2	92	77	85	67	77	95	85	69	71	78	68	79
3	97	83	83	58	89	91	83	88	85	82	73	77
4	97	87	78	65	82	89	78	79	74	81	79	80
5	87	78	89	59	81	96	89	85	73	75	69	69
6	98	94	83	66	92	93	83	89	89	81	73	74
7	94	86	86	69	85	95	86	81	78	82	81	83
8	90	95	90	68	79	91	90	93	74	74	69	68
9	85	77	76	62	87	88	76	79	79	80	71	69
10	92	91	87	68	75	92	87	84	72	80	77	75
11	99	87	93	75	91	98	93	81	70	79	73	70
12	91	85	88	64	88	94	88	89	90	84	82	86

According to the second-level indicator, the following three groups of fuzzy relations are obtained:

$$R_1 = \begin{bmatrix} 0.833 & 0.167 & 0.000 & 0.000 & 0.000 \\ 0.167 & 0.667 & 0.167 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.083 & 0.750 & 0.167 \\ 0.167 & 0.583 & 0.250 & 0.000 & 0.000 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0.833 & 0.167 & 0.000 & 0.000 & 0.000 \\ 0.167 & 0.667 & 0.167 & 0.000 & 0.000 \\ 0.083 & 0.583 & 0.250 & 0.083 & 0.000 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 0.083 & 0.167 & 0.750 & 0.000 & 0.000 \\ 0.000 & 0.667 & 0.333 & 0.000 & 0.000 \\ 0.000 & 0.167 & 0.583 & 0.250 & 0.000 \\ 0.000 & 0.333 & 0.417 & 0.250 & 0.000 \\ 0.167 & 0.250 & 0.583 & 0.000 & 0.000 \end{bmatrix}$$

We use the corresponding weight vector to carry on the fuzzy transformation $\tilde{Q}_i = P_i \circ$, and then normalized it to get Q_i , thereby the fuzzy evaluation relation of the first-level indicator is obtained:

$$R = [Q_1, Q_2, Q_3]^T = \begin{bmatrix} 0.284 & 0.358 & 0.122 & 0.178 & 0.040 \\ 0.399 & 0.452 & 0.126 & 0.023 & 0.000 \\ 0.021 & 0.329 & 0.524 & 0.126 & 0.000 \end{bmatrix}$$

We carry on the fuzzy transformation and normalization for R , and then we get the overall fuzzy evaluation:

$$Q = [0.235, 0.382, 0.259, 0.109, 0.015].$$

These results demonstrated that 23.5% of those surveyed believe that the city is Excellent, 38.2% considered Good, 25.9% considered Medium, 10.9% considered Worse, 1.5% considered Worst. Finally, we use Q as the input to the BP network and the output was 0.72. We usually use the percentile system to convert it, and get the city's overall score was 72 points.

Similarly, score results of Lobito as follows:

Table 8. Score results of Lobito

Number	U11	U12	U13	U14	U21	U22	U23	U31	U32	U33	U34	U35
1	71	71	67	91	73	93	90	85	78	64	61	82
2	79	76	65	81	68	95	87	86	64	59	62	75
3	79	77	59	83	67	95	88	85	67	59	57	73
4	68	69	69	86	66	88	85	82	68	58	66	79
5	75	76	54	76	69	98	93	90	83	73	70	82
6	70	69	61	78	59	97	89	75	64	55	59	69
7	72	74	60	87	68	93	80	83	69	57	67	81
8	66	82	66	79	67	85	82	84	75	67	72	68
9	73	75	66	80	68	96	79	69	64	58	62	73
10	78	80	56	90	69	95	79	72	67	56	69	69
11	70	72	61	89	63	92	83	74	66	59	57	80
12	70	77	61	85	59	90	81	82	69	57	67	79

Three groups of fuzzy relations about second-level indicator of urban Lobito as follows:

$$R_1 = \begin{bmatrix} 0.000 & 0.000 & 0.833 & 0.167 & 0.000 \\ 0.000 & 0.167 & 0.667 & 0.167 & 0.000 \\ 0.167 & 0.583 & 0.250 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.083 & 0.750 & 0.167 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0.833 & 0.167 & 0.000 & 0.000 & 0.000 \\ 0.167 & 0.667 & 0.167 & 0.000 & 0.000 \\ 0.083 & 0.583 & 0.250 & 0.083 & 0.000 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 0.000 & 0.083 & 0.167 & 0.750 & 0.000 \\ 0.000 & 0.000 & 0.083 & 0.167 & 0.750 \\ 0.000 & 0.000 & 0.167 & 0.583 & 0.250 \\ 0.000 & 0.333 & 0.417 & 0.250 & 0.000 \\ 0.000 & 0.083 & 0.250 & 0.417 & 0.250 \end{bmatrix}$$

The fuzzy evaluation of the first-level indicator is as follows:

$$R = [Q_1, Q_2, Q_3]^T = \begin{bmatrix} 0.020 & 0.194 & 0.482 & 0.257 & 0.047 \\ 0.399 & 0.452 & 0.126 & 0.023 & 0.000 \\ 0.000 & 0.112 & 0.215 & 0.439 & 0.234 \end{bmatrix}$$

The overall fuzzy evaluation is as follows:

$$Q = [0.139, 0.258, 0.274, 0.238, 0.091]$$

Finally, we get the city's overall evaluation score is 53 points.

C. Assessing Intelligent Growth Plans

The smart growth evaluation method which is based on the fuzzy theory and neural network, not only evaluate the current development of the city, but also can analyze the fuzzy evaluation matrix in mathematical model to find out the deficiency in the development of the city. At the time of making the development plan, we should find out the existing problems in the development of the city from the score of each indicator in the evaluation model. Meanwhile, we should combine the urban development planning data in recent years to analyze the development space of each indicator and make sure that the development plan is feasible.

According to the scoring results of the assessment of experts about two cities, we summarize the scoring of each evaluation indicator, the results are shown in Fig. 4.

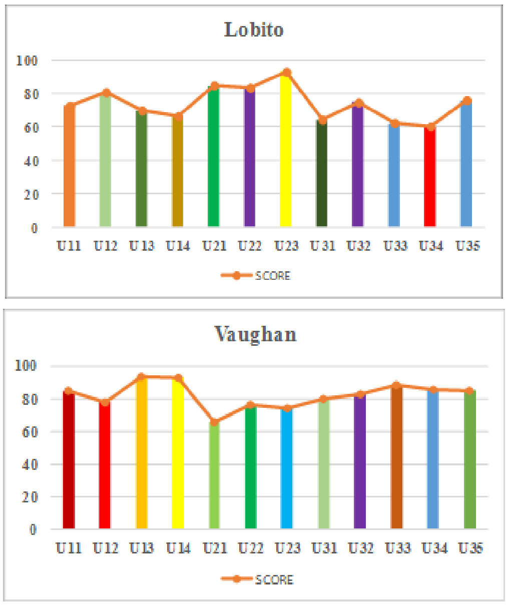

Fig. 4. The scoring of each evaluation indicator

Each project is related to a number of indicators. We predict that 20 years later, by the plan one - the government increased the supply of infrastructure and public transport, the number of beds per thousand people and the number of schools per thousand people, which are increased by 40%. By plan two - the rational development and utilization of land, agricultural land area and green coverage increased by 30%, while the air quality improved by 10% with the increasing of green space; By plan three - environmental protection, air quality improved by 30%; By plan four - human resources training and employment guidance, per capita GDP, per capita income and employment rate are increased by 40%, meanwhile, due to the annual per capita consumption and the number of cars per thousand people which are related to these three indicators, also corresponding increase of 30%. Last, add these to the previous model, we can conclude that the city's overall evaluation score increased by about 35%.

VI. Conclusion

Smart growth evaluation model based on fuzzy theory and neural network advantage has the following advantages:

(1) Dynamic particle swarm algorithm and fuzzy theory are used to extract and optimize the possible indicators, which improves the accuracy of model evaluation.

(2) We use fuzzy comprehensive theory and BP neural network on the method of combining to evaluate smart growth, which eliminate the influence of human subjective factors on the evaluation system to the maximum extent.

(3) It is important to consider three factors: weak points, high sensitivity indicator, development space, when we make development plan for the two cities, and rank the smart growth plan as the most potential to the least potential.

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