Model of Land Suitability Evaluation Based on Computational Intelligence

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Abstract  A novel model of land suitability evaluation is built based on computational intelligence (CI). A fuzzy neural network (FNN) is constructed by the integration of fuzzy logic and artificial neural network (ANN). The structure and process of this network is clear. Fuzzy rules (knowledge) are expressed in the model explicitly, and can be self-adjusted by learning from samples. Genetic algorithm (GA) is employed as the learning algorithm to train the network, and makes the training of the model efficient. This model is a self-learning and self-adaptive system with a rule set revised by training.

Keywords  land suitability evaluation; computational intelligence; fuzzy neural network, genetic algorithm

Introduction

Computational intelligence is a kind of technology that simulates the mechanism of human intelligence, biological evolution, and intelligent behaviors. Three typical branches are artificial neural network, evolutionary computing, and fuzzy logic.

According to reasoning mechanism, the ordinary methods of land suitability evaluation can be divided into two groups: one is based on symbolic logic, knowledge and rules, and the other is based on self-learning mechanism of computational intelligence system. The former includes empirical model, fuzzy comprehensive assessment[1,2], etc. The latter mainly refers to artificial neural networks (ANN). The fuzzy neural network (FNN) model is a new model that integrates fuzzy logic and neural network, which is used widely, such as intelligent control, system fault diagnosis[3], classification of remote sensing images[4], etc. FNN is newly employed in land suitability evaluation[5]. The main problems of these methods are: ① the symbolic logic methods are not self-learning, and depend on knowledge and experience; ② the ANN model is independent of known knowledge, and is a “black box” because it has an over-complicated reasoning procedure, and the rules trained are hard to be interpreted; ③ existing FNN, for example, the universal FNN, have a rules combinatorial explosion problem when the system has many input values (e.g., land suitability evaluation). This is also called “rules disaster”, which will cause an over-complicated and clumsy system. The FNN model proposed in Reference [5] avoids this problem, but it has a complex training algorithm and hidden rules.

A FNN model of land suitability evaluation based on fuzzy comprehensive assessment and ANN theory is built in this paper. This model has a clear reasoning process and no rules explosion problem, trained by GA algorithm. The model can take full advantage of
given knowledge, at the same time, it can learn from samples and correct original incomplete rules.

1 Building of FNN model

1.1 Principle of model

FNN model has different types due to different application purposes and design approaches. In this paper, we build FNN according to fuzzy comprehensive assessment. The main procedure of fuzzy comprehensive assessment model in land suitability evaluation includes: at first, design the membership functions of each factor to suitability grades and build the matrix of degrees of membership; make the matrix of factors’ weights, which represent the influencing degrees of factors. And then, calculate the matrix of comprehensive evaluation, the product of forenamed two matrixes. The resulting matrix represents degrees of membership of land evaluative parcels to each grade, and the grade that has the maximum degree of membership is chosen as the final grade. The figures of membership functions are shown in Fig. 1. Now we will design a FNN model according to these three steps, same to fuzzy comprehensive evaluation: calculating degrees of membership of each factor, calculating comprehensive membership degrees, and determining of final result.

The activation functions and weights of neurons in each layer are described as the following:

The first layer is input layer. \( y_i^{(0)} \), the output of neuron \( i \), is equal to the input:

\[
y_i^{(0)} = x_i
\]

where \( x_i \) is the input variable \( i \), which represents the value of factor \( i \). There are \( n \) neurons in this layer when there are \( n \) factors.

The second layer is the layer of membership functions,

\[
s_{ij}^{(1)} = \frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}
\]

\[
y_{ij}^{(1)} = \exp(s_{ij}^{(1)})
\]

where \( s_{ij}^{(1)} \) represents the input of the membership function neuron of grade \( j \) of factor \( i \); \( y_{ij}^{(1)} \) is the output; \( m_{ij} \) represents the center of the membership function; and \( \sigma_{ij} \), the variance. Suppose there are 4 grades of each factor, 4 fuzzy sets of each input, so each factor has 4 corresponding neurons (i.e. 4 membership functions). There are total \( 4n \) neurons in this layer.

The third layer is fuzzy reasoning layer, which sums the membership degrees of factors according to weights.

\[
s_{k}^{(2)} = \sum_{i=1}^{n} w_{ik} y_{ij}^{(1)}, \quad j = k
\]

\[
y_{k}^{(2)} = s_{k}^{(2)}
\]

where \( s_{k}^{(2)} \) represents the input of neuron \( k \) in the third layer; \( y_{k}^{(2)} \) is the output; \( w_{ik}^{(2)} \) represents the weight of factor \( i \), so the 4 weights connecting to membership function neurons of factor \( i \) have the same value. There are total 4 neurons in this layer.

The fourth and the fifth layers are used to find the maximum membership degree and give the result grade, the final result of the comprehensive evaluation. In the fourth layer,

\[
y_{l}^{(3)} = \max(y_{k}^{(2)})
\]

\[
y_{l}^{(3)} = y_{k}^{(2)}, \quad k = l - 1, \quad l = 1, 2, 3, 4
\]

where \( y_{l}^{(3)} \) is the output of neuron \( l \) in the fourth layer; and \( y_{0}^{(3)} \), the first. “max” is the function to get the maximum.

In the fifth layer,

\[
y_{m}^{(4)} = \text{int}(y_{l}^{(3)} - y_{l}^{(3)} + 1), \quad l = 1, 2, 3, 4
\]

where \( y_{m}^{(4)} \) is the output of neuron \( m \) in the fifth layer;
2 Genetic training of FNN model

BP is a widely used training algorithm of ANN, but it can only be employed on the ANN model whose activation functions are all differentiable. In this model, “max” and “int” functions are employed, which are not differentiable. GA (genetic algorithm) is very capable of solving those complicated optimization problems, which have large searching space or a non differentiable objective function. So GA is employed as a training algorithm of the FNN model, which can make the model converge quickly.

2.1 Principle of GA training

Variables of the FNN model proposed in this paper include parameters of membership functions and factors’ weights. Genetic training of the FNN model includes the following three steps: encode the model’s variables and generate the original population, get the optimized individual that matches given error limitations by genetic operations (selection, crossover and mutation), decode the chromosome and get the trained FNN model.

2.2 Genetic training algorithm of FNN and its improvement

1) Coding. The variables in the membership functions layer of FNN are the center and variance of each membership function. But the membership functions of a factor can be determined only by the grades boundaries (i.e. \( c_1, c_2, c_3 \) in Fig 1) of this factor because of the relativity between variables of membership functions when the type of membership function is chosen. For the convenience of calculation, these variables are used to describe membership functions.

\[
\Delta c_1 + \Delta c_2 + \Delta c_3 < c_4 - c_1, \quad \Delta c_4, \Delta c_5, \Delta c_6 > 0 \quad (9)
\]

In the fuzzy reasoning layer, weights of factors are variables, and their sum is 1:

\[
a_1 + a_2 + \cdots + a_n = 1, \quad a_1, a_2, \cdots, a_n > 0 \quad (10)
\]

where \( a_1, a_2, \cdots, a_n \) represent weights of factors. In coding, we arrange these variables \( \Delta c_1, \Delta c_2, \Delta c_3, \) and \( a_1, a_2, \cdots, a_n \) orderly and make chromosomes.

2) Fitness calculation. Fitness function is used to evaluate chromosomes in GA. In this paper, the reciprocal of the model MSE (mean square error) of training samples is used as a fitness function. The MSE of FNN, described by chromosome \( x_i \), is given by:

\[
E(x_i) = \frac{1}{N} \sum_{n=1}^{M} \frac{1}{2} (d_m^{(n)} - z(m))^2 \quad (11)
\]

where \( E(x_i) \) represents MSE; \( d_m^{(n)} \) is the expectative output of neuron \( m \) in the output layer of sample \( n \); and \( z_m^{(n)} \), the actual output; \( M \) is the number of neurons in the output layer; \( N \) is the number of samples. The fitness function is:

\[
f'(x_i) = 1 / E(x_i) \quad (12)
\]

To avoid local minima, according to Goldberg and Richardson, fitness-sharing model can be used to adjust the fitness of individuals, simulating lives’ evolution in niche. Please refer to References [6,7].

3) Selection. Similar to natural selection in biology, selection is used to choose those chromosomes, which have higher fitness, to be crossed and mutated to generate the next generation. Roulette wheel selection is used widely. According to this method, the selection probability of a chromosome is given by:

\[
P_i = f(x_i) / \sum f(x_i) \quad (13)
\]

where \( x_i \) represents chromosome \( i \); \( f(x_i) \) is its fitness; and \( \sum f(x_i) \) is the sum of chromosomes’ fitness. Selection probability is used to select individuals. This method is clear and simple, but the potential problem is that the best individual in the current generation may not be selected, or may be destroyed by crossover or mutation. It has been proven that the simple GA cannot converge by the probability of 1 when the Roulette wheel method is employed in the selection. But when the best individual is always preserved in each generation, the global best individual will be found definitely. In this paper, the best individual is selected and put into the next generation directly.

4) Crossover. Selection (copy) can be used to select the excellent individuals from former generations, but not create new ones. Crossover is used to create new individuals by crossing two chromosomes, simulating
natural reproduction. A series of weights connected to the same neuron of a network are working together, called a logical subset. It is testified that FNN model can get better evolution when each logical subset is treated as an independent unit in genetic operation. In the membership function layer of FNN, each of the four neurons corresponding to the same factor, which represent four membership functions of the factor, make a logical subset. There are a total of $n$ logical sets in this layer if there are $n$ factors. In the fuzzy reasoning layer, the $n$ factors’ weights, whose sum is 1, make a logical subset. So there are total $n + 1$ logical subsets in this model. In crossover, two selected chromosomes exchange their one or more pairs of corresponding subsets and new chromosomes are created.

5) Mutation. Similar to crossover, the operating unit of mutation is also a logical subset. Adding a random number to each of its element mutates the logical subset. Mutation should not violate Eqs.(9) and (10).

2.3 Flow of genetic training

We employ improved GA to train the FNN model proposed in this paper. The flowchart of the genetic training is show in Fig.3.

3 Application of the model

Land suitability evaluation is a kind of intelligent spatial decision support system, which should analyze land’s natural, social and economic conditions and their distribution. The frame of an intelligent land suitability evaluation system based on FNN and GIS is shown in Fig.4.

![Flowchart of FNN genetic training](image)

![Intelligent land evaluation based on GIS and FNN](image)

The land suitability evaluation in Qionghai City, Hainan Province of P.R. China, is used as a study case. The land suitability evaluation in Qionghai is a multi-aimed evaluation, including paddy field evaluation, dry land evaluation, forest evaluation and so on. Factors system is determined for each kind of evaluation. The evaluation for paddy field use is used to test the FNN model. The original factor system of paddy field evaluation is shown in Table 1.

Values in Table 1 should be standardized as real numbers between 0 and 1 in order to fit in with neural networks. The FNN model is built based on the factors system, as seen in Fig.2. There are 9 neurons in the input layer.
layer, representing 9 factors. Each factor has 4 grades, so there are total $4 \times 9 = 36$ neurons in the membership functions layer. The outputs of each of the 4 neurons connected to each factor represent degrees of membership of this factor. In the third layer, there are 4 neurons, whose outputs are degrees of membership of a parcel to 4 grades. The fourth layer and the fifth layer find out the maximum of degrees of membership, and the output is the comprehensive evaluation result. The FNN model is initialized based on the original factors system.

### Table 1  Original factors system of paddy field evaluation

| Factors                      | Weights | I      | II     | III    | IV     |
|------------------------------|---------|--------|--------|--------|--------|
| Soil organic content/%       | 0.2     | > 3    | 3~2    | 2~1    | < 1    |
| Soil texture                 | 0.1     | Heavy or middle loam | Light loam or clay | Sandy loam | Clay or sandy soil |
| Water conservancy            | 0.2     | Very good | Good   | Ordinary | Poor   |
| Thickness of tilth/cm        | 0.2     | > 30   | 30-20  | 20-10  | < 10   |
| Slope grade (/°)             | 0.1     | < 1    | 1-2    | 2-3    | > 3    |
| Nitrogen                     | 0.05    | > 0.15 | 0.15-0.10 | 0.10-0.05 | < 0.05 |
| Phosphor                     | 0.05    | > 0.15 | 0.15-0.10 | 0.10-0.05 | < 0.05 |
| Kalium                       | 0.05    | > 2    | 2-1.0  | 1.0-0.5 | < 0.5  |
| PH                           | 0.05    | < 5.0  | 5.0-7.0 | 7.0-8.0 | > 8.0  |

In consideration of samples’ representation, all training and test samples were collected mainly by random, under the condition of rough balance of local distribution, land utilization, and land suitability. There are a total of 200 samples, including 140 training samples and 60 testing samples. The model learns from training set by improved GA. Adding random numbers to the chromosome representing the original FNN creates new ones, and size of the original population is 20. 70% of the selected individuals that are to be crossed, and the others are to be mutated. Random offset in mutation is in $[-0.2, 0.2]$. Through 30 generations, MSE of the model is less than 0.05 (i.e. the fitness is larger than 20). Rules can be generated from the trained FNN model. Because these rules are revised from the original rules set by learning from samples, they are more objective. The revised factors system is shown in Table 2. The samples contribution and the comparison of evaluation result of before and after training is shown in Fig.5.

### Table 2  Final factors system of paddy field evaluation after training

| Factors                      | Weights | I      | II     | III    | IV     |
|------------------------------|---------|--------|--------|--------|--------|
| Soil organic content/%       | 0.2     | > 3    | 3-2    | 2-1    | < 1    |
| Soil texture                 | 0.1     | Heavy or middle loam | Light loam or clay | Sandy loam | Clay or sandy soil |
| Water conservancy            | 0.2     | Very good | Good   | Ordinary | Poor   |
| Thickness of tilth/cm        | 0.2     | > 20   | 20-15  | 15-10  | < 10   |
| Slope grade (/°)             | 0.1     | < 1    | 1-2    | 2-4    | > 4    |
| Nitrogen                     | 0.05    | > 0.15 | 0.15-0.10 | 0.10-0.05 | < 0.05 |
| Phosphor                     | 0.05    | > 0.18 | 0.18-0.09 | 0.09-0.04 | < 0.04 |
| Kalium                       | 0.05    | > 1.8  | 1.8-0.9 | 0.9-0.6 | < 0.6  |
| PH                           | 0.05    | < 5.5  | 5.5-7.0 | 7.0-8.2 | > 8.2  |

From Fig.5, in the evaluation result map before training, we can see that there are many samples that have different grades compared with the region they are located in. Most of them are located in an inter-grade area or scattered in a large region. This is caused by the difference between the factors system and the samples. Experiential knowledge is not objective in some sense. We see that this is corrected by training from the result map after training. Evaluation result is coincident with most samples.

Comparing with other models, the model in this paper has many virtues (Table 3).

### Table 3  Comparison of models

| Models                      | Model building | Self-learning | Rules       | Convergence          |
|-----------------------------|----------------|---------------|-------------|----------------------|
| Fuzzy comprehensive assessment | Simple         | No            | Clear       |                     |
| ANN                         | Complex        | Yes           | Non-clear   | Slowly, has minima   |
| Ordinary FNN                | Rules disaster problem | Yes           | Semi-clear  | Fast, has a few minima |
| The FNN in this paper       | Simple         | Yes           | Clear       | Faster, has few minima |
4 Conclusions and future work

In this paper, we build a FNN model for land suitability evaluation based on ANN and fuzzy comprehensive assessment and propose a training algorithm based on improved GA. The model in this paper has the following advantages: ① reasoning process is clear; ② no “rules disaster” problem; ③ GA training revises original rules, and these rules are readable; ④ the model converges faster, and has no local minima.

The FNN model proposed in this paper can still be improved in further research. We can also employ BP to train the FNN model when the “max” function and the “int” function are replaced by corresponding continuous functions. The model will have better searching ability both globally and locally when integrated with GA and BP. Spatial statistics analysis and interpolation of the samples are also to be studied further.

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