A Forest Health Assessment Method Based on ABC-MNN

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***Abstract*—To better support forest sustainable management, this paper explores the technical framework for forest health assessment, and then focuses on how to better execute the evaluation part of this technical framework. Modular neural networks (MNN) have been shown to be more efficient for classification problems than the conventional monolithic artificial neural network. Therefore, this was used in the evaluation part of this technical framework. Unfortunately, the conventional back propagation (BP) algorithm which is commonly used to train each single artificial neural network (ANN) in MNN has slow convergence speed and the local minimum. To solve this issue, the artificial bee colony (ABC) algorithm is introduced. By combining the robust global searching ability of ABC algorithm with the strong nonlinear mapping and learning ability of BP algorithm, the hybrid ABC-BP algorithm was adopted as the learning algorithm of each single ANN in MNN. In summary, this paper presents a new model of MNN based on the hybrid ABC-BP algorithm (ABC-MNN, for short) to be used for forest health assessment. Its effectiveness is supported and illustrated in the accompanying experimental results.**

***Index Terms*—forest health assessment, modular neural networks, artificial bee colony, back propagation**

I. Introduction

While forest health assessment has widely become an effective approach for supporting forest sustainable management, differing definitions and concepts of the forest health has a direct influence on its research. This paper adopts the generalized concept of a healthy forest area or forest ecosystem is one where the forest resource can meet the reasonable needs of the people and also can maintain its own stability and healthy development.

Researchers have put forward various kinds of assessment index systems and assessment methods of forest health according to different forest types, management objects and regional culture [1]. The three-layer assessment index system has been commonly accepted as a suitable for forest health and therefore, this paper aimed at finding a similar structure.

Forest health is influenced by many factors and the complex interactions between these factors, which make assessment and classification very difficult. The artificial neural network (ANN) is commonly used in various classes of classification problems, and has ideal generalization performance due to its self-learning, self-organization, self-adaptability and strong nonlinear mapping capabilities. Therefore, ANN is especially appropriate to deal with the complexity of forest health assessment.

Back propagation (BP) algorithm is commonly used to train ANN [2][3]. But the conventional BP algorithm has some disadvantages: slow convergence speed and the local minimum, which both lead to lower training and testing accuracy. To solve this issue, the artificial bee colony (ABC) algorithm is combined with BP algorithm. ABC algorithm has the excellent global optimization ability and is very suitable for solving the continuous space optimization problem. The ABC algorithm has been commonly used in the optimization of synaptic weights from an ANN [4][5][6]. In this paper, a hybrid ABC-BP algorithm is used to support the evaluation part of technical framework. Experiments show that the ABC-BP algorithm has higher convergence speed.

However, the monolithic neural network based on ABC-BP algorithm still has serious learning problems. Proper monolithic artificial neural network design may solve the problem of forest health assessment, but these do not scale well with increasing complexity. Modular neural network (MNN) has been shown to be more efficient for certain classes of classification problems [7][8][9]. Therefore, this paper proposed and tested a model of MNN based on ABC-BP algorithm (ABC-MNN, for short) as the evaluation part of technical framework. Compared to the monolithic artificial neural network

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based on ABC-BP algorithm, ABC-MNN had higher the training and testing accuracy.

The paper is organized as follows: in section 2, the technical framework for forest health assessment is explored. In section 3, the basics of BP and ABC algorithms are introduced as well as the proposed hybrid ABC-BP algorithm. In section 4, the ABC-MNN for forest health assessment is presented. Section 5 presents the experimental results using the forest health assessment problem of Beijing badaling forest farm. Finally, the conclusions of the work are presented in Section 6.

II. Technical Framework for Forest Health Assessment

A suitable technical framework must be built to evaluate the status of a forest area or ecosystem. The technical framework for forest health assessment is given in Figure 1. It has three components: the assessment index system, the data pre-processing, and the evaluation.

As mentioned before, the assessment index system that is commonly used has three layers. The first is the target layer, where the target value indicates the health status of a forest area or a forest ecosystem and its range is the set of categories {*health*, *medium-health*, *subhealth*, *poor health*, *other*}.

The second layer is the criteria layer. These will vary depending on the understanding of the factors affecting forest health. For example, in literature [11], the criteria are divided into five types: health and vitality of ecosystems, biomass and carbon sequestration function of forests, biodiversity of forests, function and value of forests, and ability of social support for forest health. In literature [12], the criteria include integrity of community structure, stability of forest stands, and growth of forest stands.

The third layer is the index layer. Like the criteria layer, this can also vary. However, the structure of the assessment index systems is fixed, and its specific details won't affect the assessment method. Therefore, aiming at a general three-layer assessment index system, the second and third parts of the technical framework are studied later in this paper.

For the data pre-processing, fuzzy theory and rough set theory were employed to quantify the training sample data and carry out the attribute reduction before doing the evaluation part. This is because the training sample dataset may be immeasurable, fuzzy, and/or redundant. Modular neural network (MNN) is used in the evaluation phase. This is the core part of the technical framework, and this paper tackles how to train the MNN later.

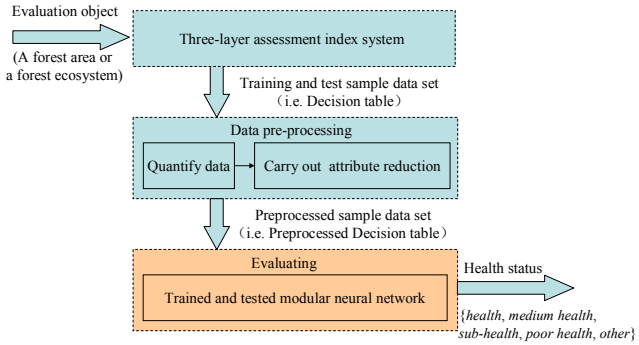

Figure 1. The Technical Framework for Forest Health Assessment.

III. Neural Network Learning Algorithm Based on ABC

A. BP Algorithm

Back propagation (BP) algorithm is commonly used to train artificial neural network (ANN). The training process has two phases. The first phase is the forward pass, which is used for network computing. The BP neural network is initialized by setting up all of its synaptic weights to be random numbers -- say between -1 and +1. The input of the network is the vector X=(x_1, x_2, …, x_n), where n is the number of the sample features. Next, the vector X is applied to the network and the output is calculated. At this stage, the transfer function of the hidden layer neurons and the output layer neuron is a sigmoid function.

The second phase is the reverse pass, which is used to improve the synaptic weights of BP neural network. If the error e is not able to meet the error goal, the synaptic weights of the whole BP neural network should be improved from back to front layer by layer, which ensures that the error e is always reduced. The error e is calculated as follows:

$$e = 1/2 \times (EO_y - O_y)^2 \tag{1}$$

In Formula (1), O_y and EO_y represent the actual output and the expected output of the only output neuron y, respectively. The two phases are repeated until the error e can meet the the error goal.

B. ABC Algorithm

ABC algorithm is a swarm intelligent optimization algorithm and has among its advantages easy understanding, simplicity for implementation, and excellent global optimization ability [13]. It is especially suitable for solving the continuous space optimization problem.

The ABC algorithm has three phases: employed bee phase, onlooker bee phase, and scout phase [14][15][16]. These are executed iteratively until the number of cycles is equal to the maximum cycle number *MCN*. In the employed bee phase, according to the rule of greedy selection, the best solution in her memory are compared with the new solution. Provided that the fitness of the new one is higher than that of the old one, the employed

bee memorizes the new solution and forgets the old one. Otherwise, she keeps the best one in her memory.

In the onlooker bee phase, the onlooker bee chooses a solution with a probability related to its fitness, and then the rule of greedy selection is also used to compare the selected solution with the new solution. Provided that the fitness of the new one is higher than that of the selected one, the bee memorizes the new position and forgets the selected one. Otherwise she keeps the selected one.

In the scout phase, provided that the fitness of a solution cannot be improved further through a predetermined number of cycles (i.e., *limit*), then that solution is assumed to be abandoned.

In conclusion, the onlooker bees choose a solution with a probability related to the fitness of that solution to ensure that most of the bees choose the search path based on the last historical information. The scouts produce a new solution randomly to ensure that some of the bees choose the search path randomly. This then ensures the diversity of the solutions and causes the search to jump out of local optimization. The employed bees with elite characteristics keep the last optimal path, which could accelerate the convergence of the algorithm and reduce the oscillation of the algorithm. The combined effect of these three kinds of bees makes the ABC algorithm have strong global searching ability and fast convergence.

C. Hybrid ABC-BP Algorithm

To improve the disadvantages of the conventional BP algorithm (e.g., being easily trapped into local minimum and slow convergence speed), a hybrid ABC-BP algorithm is introduced to train ANN. In the ABC-BP algorithm, the BP part serves as a foundation while the ABP is used to improve the initial values. This algorithm combines the robust global searching ability of ABC with the strong nonlinear mapping and learning ability of BP.

The main idea is to first optimize the synaptic weights of ANN using the ABC algorithm, and then the optimized network parameters are taken as the input to the BP algorithm. The ANN is trained constantly by this algorithm until the total error is less than the expected error ε.

In ABC-BP algorithm, a possible solution $x_i=(x_{i1}, x_{i2},\ldots, x_{iD})$ corresponds to the synaptic weights of ANN, and D is the total number of these synaptic weights. The objective function of ABC part is:

$$f_i = \sum_{k=1}^{N} e_{ik} \tag{2}$$

In Formula (2), N is the total number of the sample patterns in the training sample dataset, and e_{ik} is the corresponding error of the kth pattern for the ith solution x_i.

The ABC-BP algorithm is detailed as follows:

Input: *SN*, *MCN*, ε, the training sample dataset

Output: The solution $x_i=(x_{i1}, x_{i2},\ldots, x_{iD})$ that meets the training accuracy requirements

Process:

Step 1: Produce some random network parameters (i.e. the initial synaptic weights of ANN), which is a set of initial solutions x_{ij}, i=1…SN, j=1…D

Step 2: For each solution x_i, calculate the f_i through repeating the forward pass of BP algorithm until all the patterns have been visited

Step 3: Calculate the fitness fit_i of each solution x_i

Step 4: Cycle=1

Step 5: **Repeat**

Step 6: Produce a new solution u_i for each employed bee, and calculate its uf_i and fitness $ufit_i$

Step 7: Apply the greedy selection process between u_i and x_i

Step 8: Calculate the probability values P_i for x_i

Step 9: Produce the new solution u_i for the onlookers from the solutions x_i selected depending on P_i, and calculates its uf_i and fitness $ufit_i$

Step 10: Apply the greedy selection process between u_i and x_i

Step 11: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution

Step 12: Memorize the best solution achieved so far $x_{best}=(x_{best1}, x_{best2},\ldots, x_{bestD})$

Step 13: cycle=cycle+1

Step 14: **until** cycle=MCN

Step 15: Take $x_{best}=(x_{best1}, x_{best2},\ldots, x_{bestD})$ as the initial synaptic weights of ANN

Step 16: Make total error te=0

Step 17: Choose the first pattern from the training sample data set

Step 18: Calculate the actual output O_y

Step 19: Calculate the variations of the synaptic weights

Step 20: Calculate the new synaptic weights

Step 21: Calculate the error e between O_y and EO_y, and then add to total error te

Step 22: Provided that all patterns have been trained, then go to next step. Otherwise, go back to step 17.

Step 23: Provided that $te<\varepsilon$, then training is over and the solution $x_i=(x_{i1}, x_{i2},\ldots, x_{iD})$ that meets training accuracy requirements is used as input. Otherwise, go back to step 16.

D. MNN Model Based on ABC-BP

When the problem is relatively simple and the number of its inputs is relatively small, the conventional monolithic artificial neural network works well. But when the problem is very complicated and its inputs are enormous, the performance of the conventional monolithic artificial neural network becomes very poor [18]. The MNN is used to solve this issue. According to the conceptual "divide and conquer", the MNN combines multiple single neural networks together to solve one issue, where each single neural network is responsible for solving some part of the issue.

The hybrid ABC-BP algorithm has a strong ability to train a single neural network. This paper combines this with the MNN. The ABC-MNN has a Data Partitioning Module (DPM), an ABC-BP-NN$_i$ Module, and an

Integration Module (IM). Its architecture is shown in Figure 2.

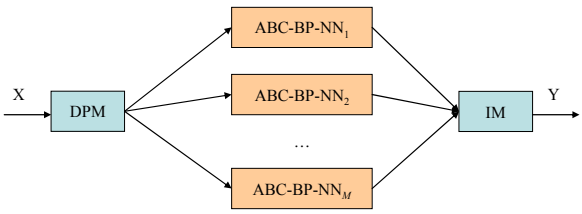

Figure 2. Architecture of the ABC-MNN

In the DPM, the bagging method is used to produce the sample dataset for multiple single neural networks. According to the proportion "4/1", the initial sample dataset is partitioned into two subsets: the training sample dataset (80%) and the testing sample dataset (20%). After that, the m training sample subsets are extracted from the training sample dataset by repeating the random sampling inside a loop for m times, and the ith training sample subset is expressed as TSi. The strategy of this random sampling is that "the number of each training sample subset TSi (i=1…M) is half of the number of the training sample dataset, so there are some training sample subsets which have the same samples. Each training sample subset TSi (i=1…M) corresponds to an ABC-BP-NNi Module.

In the ABC-BP-NN$_i$ Module, each ABC-BP-NN$_i$ is an independent ANN which is a single hidden layer forward neural network, and its structure is "*n*-*p*-1", where *p* is the number of the hidden layer node. The input of each ABC-BP-NN$_i$ is the training sample subset TS_i. At this stage, ABC-BP is used to train each ABC-BP-NN$_i$, and then the *m* different classifier h_m (i.e., the well-trained ABC-BP-NN$_i$) can be obtained.

In the IM, the "principle of majority decision" is used to integrate the classification results coming from all the classifiers h_i (i=1…M). When most of the classification results belong to the same category, the classification result of ABC-MNN is identified as this category, and its calculation formula is:

$$h(x) = \arg_{c_k} \max \sum_{i=1}^{M} u_i^{c_k}(x)$$
$$u_i^{c_k}(x) = \begin{cases} 1 & if \quad f_i(x) = c_k \\ 0 & if \quad f_i(x) \neq c_k \end{cases} \tag{3}$$

In Formula (3), x is a sample and c_k is the category of the sample.

F. Experiments and Comparison

In the literature [17], the evaluation object is the Beijing badaling forest farm. Biomass, plant diversity index and forest fire danger rating are selected to build the simplified assessment index system, and then the BP algorithm is employed to train the conventional monolithic artificial neural network, which is responsible for evaluating the health status of the forest farm. The best value of testing accuracy is about 85%.

In this paper, the sample dataset in the literature [17] are taken as the training and testing samples of ABC-BP algorithm. The convergence speeds of ABC-BP and BP algorithms are shown in Figure 3. The ABC-BP algorithm is convergent, and has better convergence speed than BP.

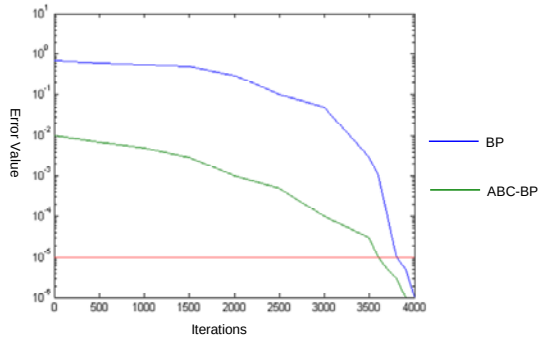

Figure 3. Comparison of convergence speed

Another experiment is performed in order to evaluate the accuracy of the ABC-MNN, as compared with the BP neural network as well as the ABC-BP neural network. The sample dataset in the literature [17] are also used in this experiment. The dataset characteristics are given in Table 1.

TABLE 1.
DATASET CHARACTERISTICS

Datasets	Observations	Features	Classes	Respective
Beijing badaling forest farm	81	3	5	6, 18, 47,8,2

TABLE 2.
COMPARISON OF TRAINING AND TESTING ACCURACY

Dataset		BP		ABC-BP		ABC-MNN	
		Training (%)	Testing (%)	Training (%)	Testing (%)	Training (%)	Testing (%)
81 samples	best	86.54	85.00	90.55	89.72	92.27	91.77
	average	85.55	81.15	88.69	87.10	91.98	90.36
	worst	84.69	73.46	86.29	83.97	91.52	89.81

The control parameters of the ABC-BP algorithm which is used to train ABC-BP neural network and multiple single neural networks ABC-BP-NN$_i$ in the ABC-MNN are set to value. Colony size (SN×2) is 40, limit is equal to SN×D where D is the dimension of the problem, and the maximum number of cycles is MCN = 1000. Experiments were repeated 30 times: 10 for the BP neural network model, 10 for the ABC-BP neural network model, and 10 for the ABC-MNN model. For each experiment, each dataset is randomly divided into two: a training set and a testing set.

Table 2 shows the best, average and worst percentage of classification for all the experiments using the BP, ABC-BP and ABC-MNN algorithms. It was observed

that the ABC-BP algorithm is able to find the better configuration for a single ANN, followed by the BP algorithm. However, the best accuracy is achieved by the ABC-MNN algorithm.

G. Conclusions

This paper presented a technical framework for forest health assessment. How to better execute the evaluation part (i.e., how to better train the artificial neural networks) in the technical framework was the main focus. To solve this issue, a forest health assessment method based on ABC-MNN was proposed. For each single artificial neural network in ABC-MNN, the hybrid ABC-BP algorithm was used as the artificial neural network learning algorithm. This algorithm combines the robust global searching ability of artificial bee colony with the strong nonlinear mapping and learning ability of back propagation (BP). This practically negated the disadvantages of conventional BP algorithm (e.g., being easily trapped into local minimum and slow convergence speed). The experimental results indicate the effectiveness of this assessment method. Utilizing an assessment model based on ABC-MNN, forest health assessment can be executed quickly and accurately, and the evaluation can help achieve better forest sustainable management.

REFERENCES

[1] Shi Ming Hui, Zhao Cui Wei, Guo Zhi Hua, et al. Review on forest health assessment [J]. Chinese Journal of Ecology, 2010, vol. 29, pp.2498-2506. (in Chinese)

[2] Qian Chen, Kama Huang, Xiaoqing Yang, et al. A BP Neural Network Realization in the Measurement of Material Permittivity. Journal of Software, vol.6, pp. 1089-1095.

[3] Fan Lin, Wenhua Zeng, Jianbing Xiahou, et al. Optimizing for Large Time Delay Systems by BP Neural Network and Evolutionary Algorithm Improving. Journal of Software, 2011 vol.6, pp. 2050-2055.

[4] Karaboga, D., Akay, B.: Artificial Bee Colony (ABC) Algorithm on Training Artificial Neural Networks. In: Proceedings of the 15th IEEE Signal Processing and Communications Applications (SIU 2007), pp. 1–4 (2007)

[5] Karaboga, D., Akay, B., Ozturk, C.: Artificial bee colony (abc) optimization algorithm for training feed-forward neural networks. In: Torra, V., Narukawa, Y., Yoshida, Y. (eds.) MDAI 2007. LNCS (LNAI), vol. 4617, pp. 318–329. Springer, Heidelberg (2007)

[6] Garro, B.A., Sossa, H., Vazquez, R.A.: Artificial neural network synthesis by means of artificial bee colony (abc) algorithm. In: 2011 IEEE Congress on Evolutionary Computation (CEC), pp. 331–338 (2011)

[7] Martinez, G., Melin, P., Castillo, O.: Optimization of Modular Neural Networks using Hierarchical Genetic Algorithm Applied to Speech Recognition. In: Proceedings of International Joint Conference on Neural Networks, Canada (2005)

[8] Fevrier, V., Patricia, M., Herman, P.: Parallel genetic algorithms for optimization of Modular Neural Networks in pattern recognition. In: IJCNN 2011, pp. 314–319 (2011)

[9] Sheikhan, M., Sha'bani, A.A.: PSO-optimized modular neural network trained by OWOHWO algorithm for fault location in analog circuits. Neural Compute Appl. (available online April 25, 2012), doi:10.1007/s00521-012-0947-9

[10] WANG ZhongChun, KANG XinGang, LUO XianXian, et al. Progress on the Assessment of Forest Health [J]. Journal o f Northwest Forestry University,2010, vol.25, pp.163-169. (in Chinese)

[11] ZHOU L J. Discussion on forest health connotation and its assessment indicators [J]. Journal of Sichuan Forestry Science and Technology, 2008, vol.29, pp.27-30. (in Chinese)

[12] JI W Y, XING S H, GUO N, et al. Health evaluation on spruce and fir forests in Miyaluo of the Western Sichuan [J] .Scientia Silvae Sinicae, 2009, vol.45, pp.13-18. (in Chinese)

[13] D. Karaboga, B. Basturk, A powerful and Efficient Algorithm for Numerical Function Optimization: Artificial Bee Colony (ABC) Algorithm, Journal of Global Optimization, Volume:39, Issue:3,pp:459-171, November 2007

[14] D. Karaboga, B. Akay. A Comparative Study of Artificial Bee Colony Algorithm. Applied Mathematics and Computation, vol. 214, pp.,108-132, 2009.

[15] Karaboga D, Basturk B. Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems [C]. LNCS: Advances in Soft Computing: Foundations of Fuzzy Logic and Soft Computing, Springer- Verlag, 2007, pp.789-798.

[16] Fei Kang, Junjie Li, Zhenyue Ma, et al. Artificial Bee Colony Algorithm with Local Search for Numerical Optimization. Journal of Software, 2011, vol.6, pp. 490-497.

[17] Li JingRui. Forest Ecosystem Health Assessment On the basis of Artificial Neural [D]. Beijing Forestry University, 2007. (in Chinese)

[18] Chen Zhuo-Ming, Wang Yun-Xia, Ling Wei-Xin, et al. Artificial Bee Colony Algorithm for Modular Neural Network. Advances in Neural Networks – ISNN 2013, Lecture Notes in Computer Science, Volume 7951, 2013, pp 350-356.

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