Development of the Neural Network for the Taxation Indices

Aleksey E. Osipenko
Ural State Forestry Engineering University
620100, Russia, Ekaterinburg,
Osipenko_alexey@mail.ru

Sergey V. Zalesov
Ural State Forestry Engineering University
620100, Russia, Ekaterinburg,
Zalesov@usfeu.ru

Natalia P. Bunkova
Ural State Forestry Engineering University
620100, Russia, Ekaterinburg,
shvaleva.natasha@mail.ru

Olga V. Tolkach
Botanical Garden of the Ural Branch of
the Russian Academy of Sciences
620100, Russia, Ekaterinburg,
tolkach_o_v@mail.ru

Gennady G. Terekhov
Botanical Garden of the Ural Branch of
the Russian Academy of Sciences
620100, Russia, Ekaterinburg,
terekhov_g_g@mail.ru

Abstract

The experience of using an artificial neural network for approximating the average height and average diameter of 187 pine stand of various ages (from 7 to 120 years) and density (from 0.4 to 10.7 thousand pieces / ha) is described in the article. As an object of research, there are pure pine stands growing in the ribbon burs of the Altai Krai territory and the Republic of Kazakhstan. All considered stands grow in dry forest growing conditions and have a different origin. Approximation of the data was carried out using the Neural Network Toolbox, which is part of the MATLAB software package. A two-layer neural network with a direct connection, a hidden layer of sigmoid-type neurons and linear output neurons was used in the course of the work. The number of neurons in the hidden layer of the network was chosen experimentally and was chosen equal to five. The aim of the work was to create a mathematical model that allows to determine the average height and average diameter of pine stand of a certain age and density. The article provides a table of the approximated values of the above taxation indices. A comparison of the approximating ability of an artificial neural network and the Mitcherlich function is made, based on the data of absolute and average approximation errors. The conclusion is drawn that the artificial neural network coped with the approximation of the taxation indices better than it was possible to do with the help of the Mitcherlich function. However, the model obtained does not describe the initial data, since the allowable limit of the mean error of approximation was exceeded.

Introduction

An artificial neural network (ANN) is a system by which software-hardware modeling of structures similar to the structure of the human brain and processes of thinking is carried out [15]. The first works related to the ANN were published back in the 40s of the twentieth century. To date, artificial neural networks are at the peak of popularity and are used in a variety of areas [16,18]. Artificial neural networks allow high-speed processing of arrays of data with a large number of variables and analyze complex non-linear systems [12, 15].

In this article, an attempt was made to apply ANN for approximating the average height and diameter of pine stands of different ages and density.

Methods and conditions of research

The object of the study is the pure pine stands of the belt forests of the Altai Krai territory and the Republic of Kazakhstan, which grow under conditions of the dry forest type in shallow hills. Studies cover stands of I-VI classes of age (from 7 to 120 years). The origin of stands is different: 80 - natural, 107 - artificial. There were no cuttings in 128 stands under consideration; felling of various (from 9 to 30%) intensity was carried out in 37 stands; there are no data on logging in 22 stands.

The taxation characteristics of 93 pine stands were obtained by the authors of the article using the method of trial plots and common methods [1, 8], the taxation descriptions of 94 stands were taken from open sources [2, 3, 4, 5, 6, 7, 9, 11 , 13, 14]. Figures 1, 2, and 3 give data on density, average height and average taxation diameter of the pine forests under consideration.

Figure 1. Density of pine stands of different ages

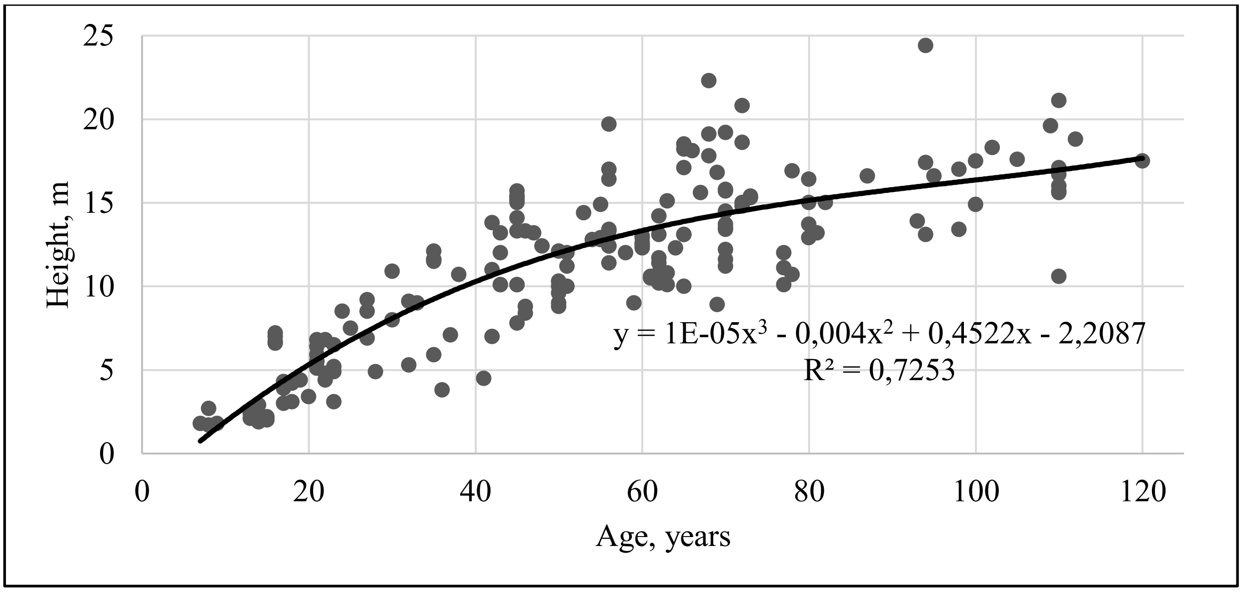

Figure 2. Dependence of the average height of stands on age

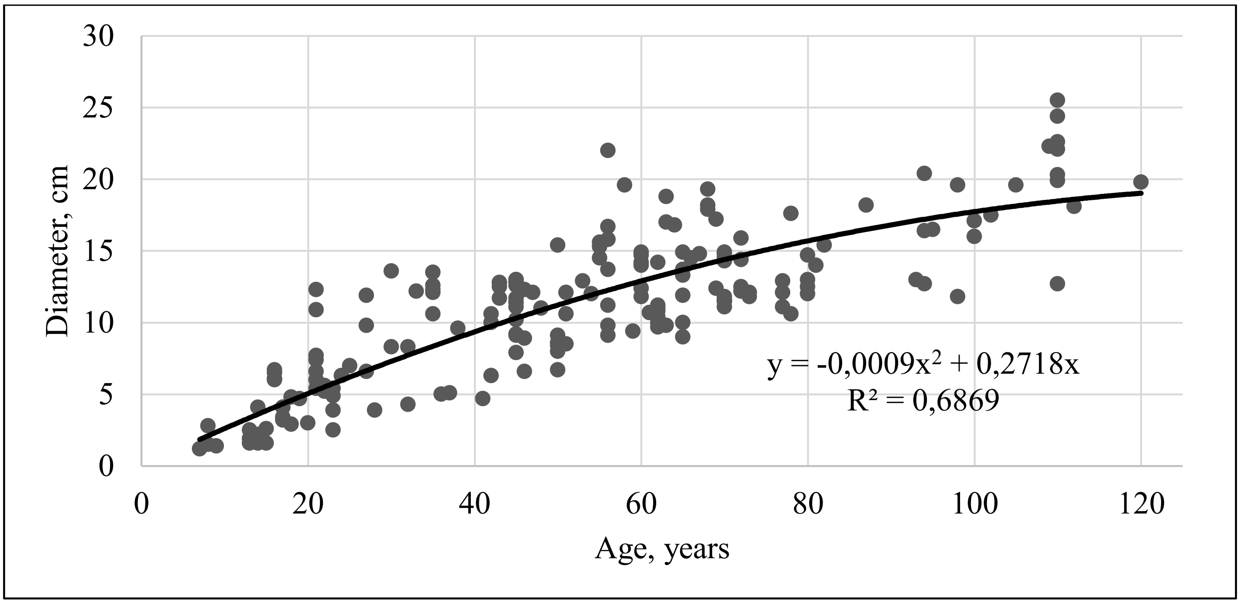

Figure 3. Dependence of the average diameter of stands on age

The data was approximated using the Neural Network Toolbox, which is part of the MATLAB software package. In the course of the work, a two-layer network with a direct link, a hidden layer of sigmoidal type neurons and linear output neurons was applied. This type of network is suitable for multidimensional mapping tasks, when specifying consistent data and a sufficient number of neurons in the hidden layer. Bayesian regularization is the used algorithm training of ANN. This algorithm usually requires more time, but can lead to a good generalization for complex, small or "noisy" data sets. The training of the ANN is stopped in accordance with the adaptive minimization of weight (regularization) [19].

Results and Discussion

The choice of the optimal number of neurons in the hidden layer is an important stage of the work, since too few of them will reduce the accuracy of the ANN, and too many can lead to an imaginary increase in the accuracy and deterioration of the network's generalizing ability [20]. In accordance with the Kolmogorov theorem [10], when creating an ANN with one hidden layer, 2N + 1 neurons are sufficient, where N is the number of input neurons. In practice, networks with one hidden layer with the number of neurons from N to 3N are more often used [12]. In this research work, N = 2, since the mean diameter and average height are approximated depending on 2 factors: age and density of the stands.

Selection of the optimal value of neurons in the hidden layer was made by repeated repetitions of the ANN learning process with different numbers of neurons. At the end of the training process, the following indices were evaluated: mean square error, the correlation coefficient, and the model's conformity to the biological features of the object of study. As a result, it was decided to use ANN with 5 neurons in the hidden layer. The root-mean-square error of the ANN for the training and test data sets was 4.5 and 4.3, respectively. The correlation coefficient (R) for both samples was 0.9. Figure 4 shows the scheme of the used neural network.

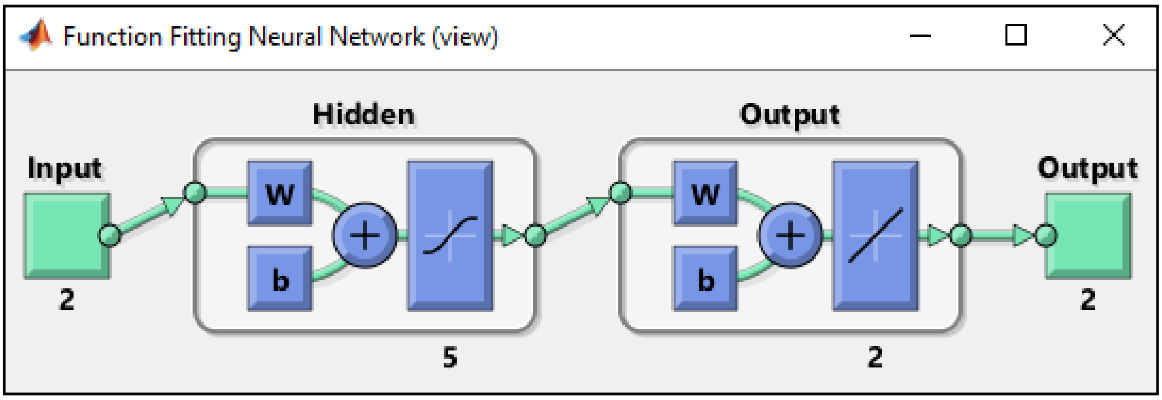

Figure 4. Diagram of an artificial neural network

As a result of training ANN, a mathematical model was obtained, which allows to determine the average height and average diameter of pine stand of a certain age and density. With the help of the latter, Table 1 was compiled.

Table 1. Approximated mean values (numerator) and diameter (denominator) of pine stands, m / cm

Age, years	Density, pcs/ha										
	0,5	1,0	2,0	3,0	4,0	5,0	6,0	7,0	8,0	9,0	10,0
10	2,0 / 3,8	2,0 / 3,3	1,9 / 2,6	1,8 / 2,1	1,8 / 1,7	1,8 / 1,4	1,8 / 1,3	1,9 / 1,2	1,9 / 1,1	2,0 / 1,1	2,0 / 1,2
20	5,5 / 7,8	5,4 / 7,3	5,2 / 6,4	5,1 / 5,7	4,9 / 5,1	4,8 / 4,7	4,8 / 4,3	4,7 / 4,1	4,6 / 3,9	4,6 / 3,8	4,5 / 3,7
30	8,7 / 11,2	8,5 / 10,5	8,2 / 9,4	7,9 / 8,5	7,6 / 7,7	7,4 / 7,0	7,2 / 6,5	7,1 / 6,1	6,7 / 5,8	6,7 / 5,5	6,6 / 5,3
40	11,3 / 13,7	11,1 / 13,0	10,6 / 11,6	10,2 / 10,4	9,8 / 9,4	9,5 / 8,5	9,2 / 7,8	8,9 / 7,2	8,6 / 6,7	8,4 / 6,3	8,2 / 6,0
50	13,4 / 15,6	13,1 / 14,6	12,5 / 13,0	12,0 / 11,6	11,5 / 10,4	11,1 / 9,3	10,7 / 8,4	10,3 / 7,7	10 / 7,0	9,7 / 6,5	9,4 / 6,0
60	15,0 / 16,8	14,6 / 15,8	13,9 / 13,9	13,3 / 12,3	12,7 / 10,9	12,2 / 9,6	11,7 / 8,6	11,3 / 7,7	10,9 / 6,9	10,6 / 6,3	–
70	16,1 / 17,8	15,7 / 16,7	14,9 / 14,6	14,2 / 12,8	13,6 / 11,2	13,0 / 9,8	12,5 / 8,6	12,0 / 7,5	11,6 / 6,6	–	–
80	16,9 / 18,7	16,4 / 17,5	15,6 / 15,2	14,8 / 13,2	14,1 / 11,4	13,5 / 9,8	12,9 / 8,5	12,4 / 7,3	–	–	–
90	17,3 / 19,6	16,9 / 18,3	16,0 / 15,9	15,2 / 13,7	14,4 / 11,7	13,8 / 10,0	13,2 / 8,5	–	–	–	–
100	17,6 / 20,6	17,1 / 19,3	16,2 / 16,7	15,4 / 14,3	14,6 / 12,2	13,9 / 10,3	–	–	–	–	–
110	17,8 / 21,7	17,3 / 20,3	16,4 / 17,6	15,5 / 15,1	14,7 / 12,9	–	–	–	–	–	–
120	17,8 / 23,0	17,4 / 21,5	16,4 / 18,7	15,5 / 16,1	–	–	–	–	–	–	–

Table 1 does not reflect the growth dynamics of stands with different densities, since the density of the stands varies with age, while the higher the initial density, the more intensive the thinning occurs [17]. However, this table allows to evaluate the taxation indices in the static, which can be useful when assigning and predicting the results of thinning.

In order to evaluate the success of the approximation of taxation indices by an artificial neural network, we find the difference between the actual real values of taxation indices (raw data) and approximated values of ANN, and comparable with the same indicator for the Mitcherlich function (Table 2). Approximation with the help of the latter was made for groups of stands with a density of 500-1500, 1501-2500, 2501-3500, 3501-4500, 4501-5500, 5501-6500, 6501-7500, 7501-10000 pieces / ha. The Mitcherlich equation has the following form:

$$Y = Y_{max}(1 - e^{-aT})^b$$

where Y_{max} is the maximum value of height (diameter), m (cm); e is the mathematical constant; a and b are the coefficients of the equation; T is the age of the stand, years.

Table 2. Data on approximation errors

Grades of absolute error values modulo, m (cm)	Number of approximated values, pcs.			
	Mitcherlich function		ANN	
	Height	Diameter	Height	Diameter
0...1	64	61	71	73
1,1…2	41	59	51	56
2,1…3	38	37	33	38
3,1…4	19	22	20	15
4,1…5	12	5	6	4
5,1…6	8	3	4	1
6,1…7	2	-	1	-
7,1…8	1	-	1	-
8,1…9	2	-	-	-
The mean absolute error of approximation, m (cm)	2,1	1,8	1,8	1,6
Average approximation error,%	21,1	20,8	18,6	18,0

The data in Table 2 indicate that the ANN has better coped with the problem of approximating the mean height and average diameter of the stand by 2.5 and 2.8%, respectively. However, the permissible limit of the mean error of approximation (10-15%) was still exceeded, which indicates that the model for describing the initial data is not good enough.

To increase the accuracy of the mathematical model of ANN, it is necessary to increase the amount of data and the number of input neurons. For example, variables such as the origin of the stand, its position relative to the terrain, the slope exposition, the presence and intensity of cutting, the area of growth and other factors affecting the average diameter and height of the stand might be added.

Conclusions

1. The artificial neural network coped with the approximation of taxation indices better than it was possible to do with the help of the Mitcherlich function.
2. The model obtained does not describe the initial data sufficiently well, since the permissible limit of the mean error of approximation (10-15%) was exceeded.
3. To increase the accuracy of the mathematical model of the artificial neural network, to approximate the average height and average diameter of the stands, it is necessary to increase the amount of data and the number of input neurons.
4. There is a need to compile a database containing as accurate and detailed a description of pine stands of belt forest.

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