PREDICTING CONE PRODUCTION IN CLONAL SEED ORCHARD OF ANATOLIAN BLACK PINE WITH ARTIFICIAL NEURAL NETWORK

GEMICI, E.[1] – YUCEDAG, C.[2*] – OZEL, H. B.[3] – IMREN, E.[4]

[1]*Department of Civil Engineering, Faculty of Engineering, Bartin University 74100 Bartin, Turkey*

[2]*Department of Landscape Architecture, Faculty of Engineering Architecture, Burdur Mehmet Akif Ersoy University, 15030 Burdur, Turkey*

[3]*Department of Forest Engineering, Faculty of Forestry, Bartin University 74100 Bartin, Turkey*

[4]*Department of Forest Industry Engineering, Faculty of Forestry, Bartin University 74100 Bartin, Turkey*

**Corresponding author*
e-mail: yucedagc@gmail.com

(Received 14th Nov 2018; accepted 11th Jan 2019)

Abstract. Seed orchards are an important seed source because they have the most important link between tree breeding and plantation forestry. The aim of this study is to evaluate the potential of Adaptive Neuro-Fuzzy Inference Systems of artificial neural networks to predict the amount of cone in clonal seed orchards of Anatolian black pine. It was found that the coefficient of determination (R^2), the mean absolute error (MAE) and the root mean square error (RMSE) of the artificial neural network model were 0.85, 14.83 and 18.85, respectively. The amount of cone in clonal seed orchards of Anatolian black pine was predicted with high efficiency through artificial neural networks. Considering the lack of forestry studies based on the artificial neural network, this study will enable further researches to provide a new perspective.
Keywords: *ANN, Bartin, flower, forestry, Pinus nigra, Yenice-Camiyanı*

Introduction

Seed orchards are an important seed source for forest plantations. They constitute the most important link between tree breeding and plantation forestry. Considerable progress has been made in understanding the reproductive biology of conifers in seed orchards (Kang, 2001; Bilir et al., 2006). These are by far the most important outlets to forestry of breeding programs and they can be useful in gene conservation. Investment in seed orchards is often by the most cost-efficient way of increasing future forest production (Bilir et al., 2009).

Researches of seed orchard are probably the most cost efficient research possible to create better forests. It is desirable to improve the function of seed orchards. There are worries about the genetic diversity of the seed orchard crops and its impact on the future forest. Low production of sound seeds is a common problem. Seed production and collection is often expensive. Basic data on seeds and cones in seed orchards and their occurrence and variation and the possible causes of variations are desirable to get a better understanding of possible improvements of seed orchard’s function, economy and impact to the forest (Bilir et al., 2009). In addition, such information is needed to establish and select seed sources and genetic conservation areas, and for future studies

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273

by governmental and private sectors because of potential of monumental plants in the species, and also to contribute potential theoretical studies on estimation of fertility variation and related variables such as effective number, status number and genetic diversity (Bilir et al., 2017).

Anatolian black pine (*Pinus nigra* Arnold. subsp. *pallasiana* (Lamb.) Holmboe) is one of the most common and important forest tree species in Turkey due to the usefulness of its wood regarding commercial uses (Sıvacıoğlu and Ayan, 2010). The species occupies about 4.2 million ha in Turkey (Anonymous, 2015). The seed for this species is mainly supplied from the current 54 seed orchards (462.8 ha) in Turkey (Anonymous, 2018).

Artificial neural network models are a powerful empirical modelling approach and yet relatively simple compared with mechanistic models (Ji et al., 2007). Artificial neural network, possessing various types, becomes crucial especially in innovating and developing better products for society as it can solve many problems that linear system is incapable to resolve (Khairunniza-Bejo et al., 2014). Artificial neural network structure is based on the human brain's biological neural processes. Interrelationships of correlated variables that symbolically represent the interconnected processing neurons or nodes of the human brain are used to develop models. Artificial neural network models find relationships by observing a large number of input and output examples to develop a formula that can be used for predictions (Pachepsky et al., 1996; Ji et al., 2007). Thus, the use of artificial neural network in forestry modeling can be efficient for predicting cone production of Anatolian black pine. In this study, we aimed at evaluating the potential of artificial neural networks for predicting the amount of cone for Anatolian black pine from clonal seed orchards.

Materials and methods

In this study, measurement results from Anatolian black pine seed orchard with Yenice-Camiyanı origin were used. This seed orchard has an area of 11.3 ha and is established within the boundaries of Bartın Forest Management Directorate in 1990 (Anonymous, 2018). In the study, 90 randomly selected samples from 120 experimental data were used to test the model while the remaining 30 were modeled. We used Average Female Flower Count (2015), Mean Diameter Value (2015), Average Number of Two-Year-Old Cones (2015) as input, and Average Number of Two-Year-Old Cones (2017) as output.

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is an artificial intelligence method created by combining of artificial neural networks that have parallel computing - learning capability and a fuzzy logic has syllogize ability. The functional based on the equilibrium between fuzzy logic as Takagi Sugeno Kang (TSK) and limited radial basis neural network (Lezanski, 2001). Output values calculated directly by weighting the input data according to fuzzy rules. These rules, which known databases, determined thanks to the computational algorithm based on neural networks. The learning algorithm of ANFIS is a mixed learning algorithm consisting of the least squares method and the back-propagation learning algorithm. The six-layer ANFIS structure is shown in *Figure 1*.

The structure of the ANFIS layers is as follows (Demirel et al., 2010; Gemici, 2011):

1. Layer (Input Layer): All input signals from each node directed to the next layers.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273

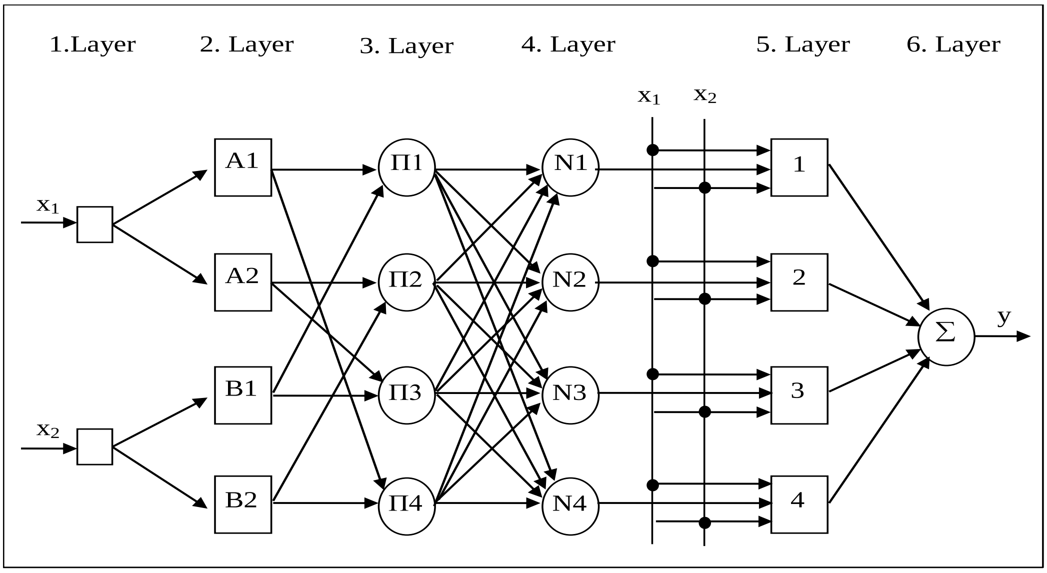

***Figure 1.** The six-layer ANFIS structure*

2. Layer (Blur Layer): Output of each node consists of the membership ratings depending on the input values and the selected membership function. The membership degrees in second layer are described $\mu_{A_j}(x)$ and $\mu_{B_j}(y)$.
3. Layer (Rule Layer): The nodes in this layer indicate the number of rules and numbers determined by the Sugeno fuzzy logic inference system. The output of each rule node (μ_i) is shown in *Equation 1,* accordingly the result of the membership degree from layer 2 is (j = 1,2) and (i = 1,…, n).

$$y_i^3 = \prod i = \mu_{A_j}(x)\ \mu_{B_j}(y) = \mu_i \qquad \text{(Eq.1)}$$

At this point, y_i^3, the output values of the third layer and "n" indicates the number of nodes in this layer.

4. Layer (normalization): The nodes in this layer accept all other nodes from the rule layer as input values and calculate the normalized value of each rule. The outputs of this layer defined as the normalized firing level. Each node in this layer is an N-labeled node. The calculation of the normalized firing level found $\overline{\mu_i}$ according to *Equation 2.*

$$y_i^4 = N_i = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i} = \overline{\mu_i}\ , \quad (i = 1, \dots, n) \qquad \text{(Eq.2)}$$

5. Layer (Rinse Layer): In this layer calculated the weighted result values of rule. At this point, the value of node "I" calculate regarding *Equation 3*.

$$y_i^5 = \overline{\mu_i}\ [p_i x_1 + q_i x_2 + r_i]\ , \quad (i = 1, \dots, n) \qquad \text{(Eq.3)}$$

(p_i, q_i, r_i) variables are the set of result parameters of the rule "i".

6. Layer (Total Layer): This layer contains only one node labelled Σ. The output value of each node summed in the layer 5 then the actual output value found.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273

The function defined the output value of the system according to *Equation 4* (Özçalık et al., 2003).

$$y = \sum_{i=1}^{n} \overline{\mu_i}\,[p_i x_1 + q_i x_2 + r_i] \quad \text{(Eq.4)}$$

Results and discussion

In order to obtain a successful ANFIS model, several types of membership function types and number of membership functions should be tried and different models should be installed. In the study, triangular, trapezoidal, gauss, gauss2 and pi membership function types as membership function were applied to the model in different number of membership functions from 1 to 6. *Table 1* shows the model parameters showing the type and number of membership functions for which the best results are obtained. In order to measure the model success, it is necessary to estimate the result parameter from the model and compare it with the actual results using the input parameters that the model has never seen before. The measured 2-year-old cones values used in the testing phase and the 2-year-old cones values obtained from the model are shown in *Table 2*. The most important parameter showing the success of the ANFIS model is the going graph showing the compatibility of the measured test data shown in *Figure 2* with the model test data. The performances of the model trials measured according to the mean absolute error (MAE), square root mean square error (RMSE) and determination coefficient (R^2).

Table 1. *Parameters of the ANFIS model generated with three input data for the estimation of average two-year cone (2017)*

INPUT	OUTPUT	First input type of MF	First input number of MF	Second input type of MF	Second input number of MF	Third input type of MF	Third input number of MF	Output MF	Error: Training MAE (number)	Error: Training RMSE (number)	Error: Training R^2	Error: Test MAE (number)	Error: Test RMSE (number)	Error: Test R^2
Average female flower count (2015) Mean diameter value (2015) Average number of two-year-old cones (2015)	Average number of two-year-old cones (2017)	gaussmf	1	gaussmf	1	gaussmf	5	constant	23.54	33.60	0.662	14.83	18.85	0.85

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273

Table 2. *The average number of two-year-old cones used as test data (2017)*

Colon 1		Colon 2		Colon 3	
Measurand	**Model**	**Measurand**	**Model**	**Measurand**	**Model**
21.3	19.51	24.1	24.88	24.5	15.58
26.7	22.55	24.7	25.34	30.8	45.90
24.5	34.37	38.4	46.95	59.2	78.50
25	34.84	44.6	57.11	84.1	67.17
37.2	50.88	63.8	74.35	105.8	120.82
32.3	72.99	81.4	62.82	164.6	130.10
44.1	46.97	117.7	148.64	210.1	199.71
53.2	53.15	169.8	131.29	130.4	121.65
73.1	85.53	100.8	74.30	76.3	92.17
99.3	61.18	73.1	72.26	108.3	126.64

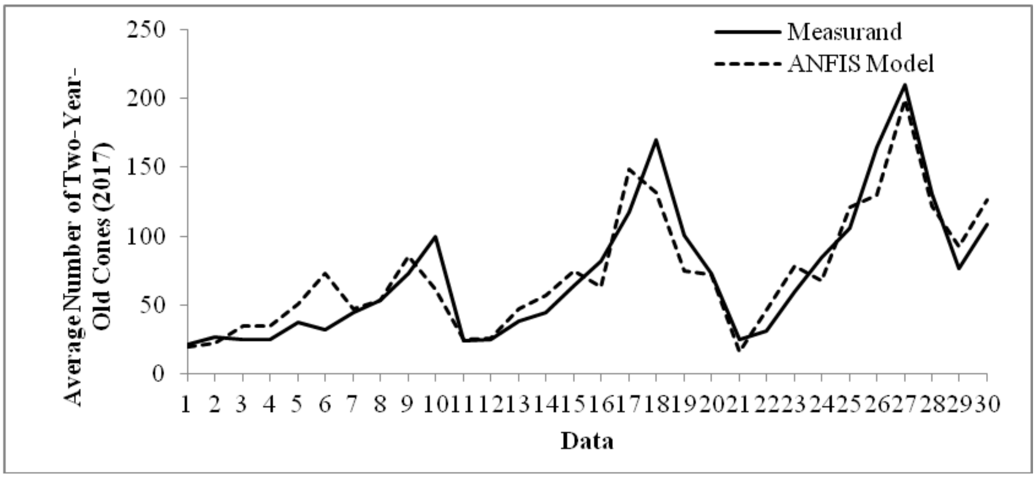

Figure 2. *ANFIS model test phase going graph*

MAE, RMSE and R^2 values found using *Equations 5–7*, respectively.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_{measurand} - y_{model}\right| \quad \text{(Eq.5)}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{measurand} - y_{model}\right)^2} \quad \text{(Eq.6)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{measurand} - y_{model}\right)^2}{\sum_{i=1}^{N}\left(y_{measurand} - y_{mean}\right)^2} \quad \text{(Eq.7)}$$

Regarding the results of the test phase, $R^2 = 0.850$, MAE = 14.83, RMSE = 18.85 in the three input ANFIS model (*Table 1*).

This ANFIS model, in 2017 two-year old cones are estimated using the number of female flowers measured in 2015, the average diameter, and the average of two-year old cones numbers. The model estimates give significant results considering the test phase values of going and scattering graphs (*Figs. 2* and *3*).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273

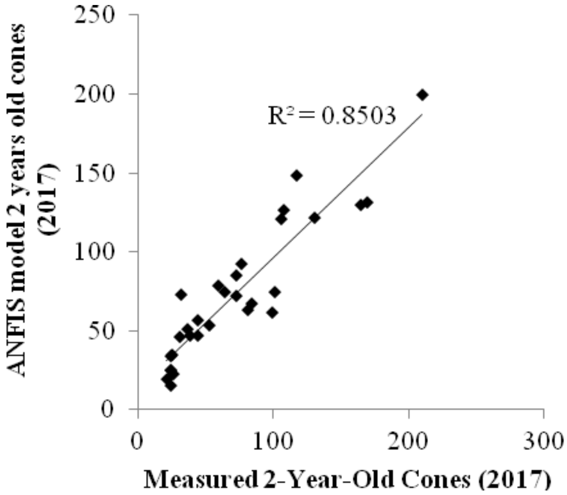

Figure 3. *ANFIS model test phase scattering graph*

Today, it is possible to estimate the amount of cones in following two years by using the number of female flowers, mean diameter and number of two-year old cones (*Table 2*). Similarly, ANN models proved to be superior for accurately predicting rice yields under typical Fujian climatic conditions (Ji et al., 2007) and for predicting the cactus pear yield (Guimarães et al., 2018). Although the new model used by Calama et al. (2016) for annual cone production surpass the detected deficiencies of previous models, accurately predicting recent decay in cone production, Kaul et al. (2005) stressed that ANN has better predicted yield variability rather than other methods.

Conclusion

The amount of cone is crucial to sustaining forestry management. In this study, predictions of the amount of cone in clonal seed orchards of Anatolian black pine are obtained with high efficiency through Adaptive Neuro-Fuzzy Inference Systems of artificial neural networks. Considered the lack of forestry studies based on the artificial neural network, this study will enable further researches to provide a new perspective.

REFERENCES

[1] Anonymous (2015): Forest Asset. Ministry of Environment and Forest. – General Directorate of Forestry, Ankara.

[2] Anonymous (2018): https://ortohum.ogm.gov.tr/Documents/.

[3] Bilir, N., Prescher, F., Ayan, S., Lindgren, D. (2006): Growth characters and number of strobili in clonal seed orchards of *Pinus sylvestris*. – Euphytica 152: 293-301.

[4] Bilir, N., Prescher, F., Lindgren, D., Kroon, J. (2009): Variation in cone and seed characters in clonal seed orchards of *Pinus sylvestris*. – New Forests 36: 187-199.

[5] Bilir, N., Çatal, Y., Tekocak, S., Cercioglu, M. (2017): Fertility variation in endemic populations of Ehrami black pine (*Pinus nigra* Arnold. subsp. *pallasiana* var. *pyramidata*). – Journal of Forestry Research 28(4): 683-686.

[6] Calama, R., Gordo, J., Madrigal, G., Mutke, S., Conde, M., Montero, G., Pardos, M. (2016): Enhanced tools for predicting annual stone pine (*Pinus pinea* L.) cone production at tree and forest scale in Inner Spain. – Forest Systems 25(3): 1-17.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273

[7] Demirel, Ö., Kakilli, A., Tektaş, M. (2010): Electric energy load forecasting using Anfis and Arma methods. – Journal of the Faculty of Engineering and Architecture of Gazi University 25(3): 601-610.
[8] Gemici, E. (2011): Experimental and computer-aided modeling of flow in natural river. – Master of Science Thesis, Erciyes University, Kayseri, Turkey.
[9] Guimarães, B. V. C., Donato, S. L. R., Azevedo, A. M., Aspiazu, I., Silva Junior, A. A. (2018): Prediction of 'Gigante' cactus pear yield by morphological characters and artificial neural networks. – Revista Brasileira de Engenharia Agrícola e Ambiental 22(5): 315-319.
[10] Ji, B., Sun, Y., Yang, S., Wan, J. (2007): Artificial neural networks for rice yield prediction in mountainous regions. – Journal of Agricultural Science 145: 249-261.
[11] Kang, K. S. (2001): Genetic gain and gene diversity of seed orchard crops. – Ph.D. Thesis, Swedish University of Agricultural Science, Umea, Sweden.
[12] Kaul, M., Hill, R. L., Walthall, C. (2005): Artificial neural network for corn and soybean prediction. – Agricultural System 85: 1-18.
[13] Khairunniza-Bejo, S., Mustaffha, S., Wan Ismail, W. I. (2014): Application of artificial neural network in predicting crop yield: a review. – Journal of Food Science and Engineering 4: 1-9.
[14] Lezanski, P. (2001): An intelligent system for grinding wheel condition monitoring. – Journal of Materials Processing Technology 109(3): 258-263.
[15] Özçalık, H. R., Uygur, A. F. (2003): Dinamik sistemlerin uyumlu sinirsel-bulanık ağ yapısına dayalı etkin modellenmesi. – KSÜ Fen ve Mühendislik Dergisi 6(1): 36-46.
[16] Pachepsky, Y. A., Timlin, D., Varallyay, G. (1996): Artificial neural networks to estimate soil water retention from easily measurable data. – Soil Science Society of America Journal 60: 727-733.
[17] Sıvacıoğlu, A., Ayan, S. (2010): Variation in cone and seed characteristics in a clonal seed orchard of Anatolian black pine [*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe]. – Journal of Environmental Biology 31: 119-123.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/1702_22672273