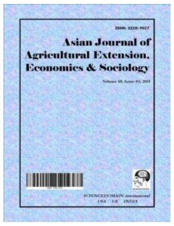

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# Estimation of Annual Industrial Wood Production Level in Forestry Operations with the Artificial Neural Network

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***Authors' contributions***

*This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.*

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## ABSTRACT

Numerous methods have been developed for estimating the production levels of forestry operations. Although these methods are classified in different ways in literature, they are fundamentally divided into two methods i.e. the quantitative and the qualitative method. In estimation studies, one of the alternative methods used instead of the traditional one is the Artificial Neural Network (ANN).

In this study, we attempted to determine the utility of the ANN method in predicting the industrial wood production yield in forestry operations according to the allowable cut. In this context, we utilized a set of variables described in the literature as influencing industrial wood production yield relative to allowable cut. These variables, which can all be measured on the basis of production units, were organized in 3 main groups; the general conditions of the stand, the natural structure of the production unit, and the production methods and tools. Using this set of variables and the Multi-Layer Perceptron (MLP) technique, various ANN models were developed for testing different degrees of learning and momentum coefficients.

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Based on the estimations performed within the scope of this study with different ANN models, we were able to identify the model which provided predictive values closest to the real values during percentage of yield estimations. During the study, it was determined that the model which performed estimations for the industrial wood yield percentage at the Günye Forestry Operations Directorate that were the closest to the actual values, with a MAPE value of 5.3%, which was the multilayered ANN model with 26 input variables, 8 neurons, 0.4 degrees of learning, and a 0.8 momentum coefficient. The error rate for the total yield percentage of the 10 production units used for testing purposes in the model was 1.7%, which is a fairly low and acceptable value. Based on these results, it is possible to state that ANN applications and models have an important potential value for use in the estimation of the yield percentage relative to allowable cut forestry operations.

*Keywords: Industrial wood; estimation methods; artificial neural networks (ANNs); oriental beech; Turkey.*

## 1. INTRODUCTION

The term production refers to the creation of products and services to meet human needs and demands, and the initial appearance of production methods in human history also corresponds to the period of humanity's first steps towards civilization [1].

Definitions regarding the production methods place emphasis on four main elements, which are, quantity, quality, time and cost. According to these definitions, the success of a business operation is defined by its ability to produce a certain quantity of products that possess suitable quality within a suitable timeframe and at a low cost [2]. However, such success in production can only be achieved by effective planning.

For a business operation, planning requires a certain level of dynamism and continuity when taking decisions towards the future [3]. Özgen (1987) defined the production planning as the process of determining all the necessary means and capabilities beforehand, as well as the policies and production processes which need to be employed, for the products and/or services that are included in the production program [4].

For businesses; the optimal usage of available resources, the minimization of production losses, and production at the desired level of quality can only be achieved through effective use of production planning. With the help of production planning, businesses can establish production systems at minimum cost, procure raw materials timely and in desired quantities, and effectively resolve problems related to the control of production and stock levels [5].

Within the context of society's needs and expectations from forest resources, forestry represents, in addition to its biological and technical characteristics, a form of economic activity; by extension, forest resources also represent a type of economic resource [6-8].

Forestry operations can be defined as a type of industry in which forest resources generated by labor and/or nature are provided as goods and services to society. Owing to this feature, forest management is, in a manner similar to other types of industries, both market-oriented and market-dependent. Due to the very high number of sectors to which the forestry sector provides raw materials both directly and indirectly, developments in the global and local markets have a direct effect on forestry operations. In this respect, it is highly important to determine and estimate not only the relations between the markets and operations and the changes in future market conditions; but also the annual industrial yield of raw material wood that will be provided to the market by the operation.

Nowadays, with the numerous different goods and services it produces, the forestry sector serves as an infrastructure as well as a source of raw materials for many other sectors. Thus, owing to this value and importance it possesses, the forestry sector represents far more than a local or regional form of business. Through the employment and added value it generates, the forestry sector plays an important role in socio-economic development at a global scale [9] (Anon, 2001).

Among the different products produced from forest resources, the one with the largest and widest marketability is raw material wood. Raw material wood, which is the main product of forestry operations, is one of the most commonly used raw material resources in numerous different branches of industry.

Örs & Keskin [10] reported that, as a raw material, wood is globally used in approximately 10,000 different types of products as either the main or secondary raw material.

The world is covered by nearly 4 billion hectares (ha) of forest area, corresponding roughly to 31% of the earth's landmass. According to the FAO's 2011 data, the total annual industrial production of round-wood in forests across the world was approximately 1.58 billion $m^3$ [11]. According to recent inventory studies, 21.5 million ha of forested land covers 28% of Turkey's entire territory, of which 11.2 million ha (52%) consists of productive forest areas. While possessing 5.4% of the world's total forested areas, Turkey has a 0.9% share in worldwide industrial round-wood production with an annual mean production of 13.5 million $m^3$ [12,13].

In Turkey, nearly 99.9% of all forests are owned and operated by the state. The operation of forest resources in Turkey is performed through forest management plans, which are defined as "the planning of a forestry operation or of its sub-operation units in accordance with the planned objectives; the monitoring and inspection of the implementation; identifying and demonstrating changes in the operation based on periodic inventory assessments; and providing sufficient information for the renewal of plans whose terms have ended" [14].

Although societies have a constant need and demand for wood, the production of this raw material depends heavily on the conditions in forests that serve as its source. Therefore, production planning for available natural resources should be performed functionally by taking into account the natural conditions in the relevant forest areas, the national policy objectives and strategies concerning forestry products, and current global demands.

The forestry management method for raw material wood that is currently implemented in Turkey is a classical and plain approach, based on the method initially developed in Central and Western Europe in the 19$^{th}$ century. This method rests mainly on imitating nature, and protecting the natural balance within the scope of this imitative approach. Thus, in parallel to the forestry approach implemented in Central and Western Europe, the planning of forest resources in Turkey focuses not on the demand for goods and services, but instead, on the organization of the supply according to the nature [15]. The goal of classical raw material wood production is achieving and maintaining the normal form of forests. To achieve and maintain this form, a variety of different methods are used, such as area control, volume control, and area-volume control [16,17].

Geray [18] considers the plans performed as based on the classical approach as erroneous plans that fail to define the existing problems accurately; fail to consider the available alternatives and their interrelations; overlook the limited resources of the operations; neglect the existing social structure; ignore the monetary aspect of the operations, as well as the time value of money; and also fail to take into account the level and composition of the demand.

Forestry operations, which assume the task of providing the society with the goods and services based on forest resources, are, in a manner similar to other business operations, both market-oriented and market-dependent entities. Due to the very high number of sectors to which the forestry sector provides raw materials, both directly and indirectly, developments in the global and local markets have a direct effect on forestry operations. In this respect, it is highly important to determine and estimate not only the relations between the markets and operations, and the changes in future market conditions; but also the annual industrial yield of raw material wood that will be provided to the market by the operation.

The timeframe of the forestry management plans employed by the state forestry operations responsible for the preservation and management of the forest resources generally range from 10 to 20 years.

In this context, the total allowable cut planned for the operation throughout the plan period will be divided by the number of the years within this period (10-20 years), thus providing the approximate amount of cut/production that is expected for each year [19].

In forestry operations, the amount and the variety of the raw material wood provided by a certain section of the forest may be different from the amount and variety provided by another section of the forest with the same allowable cut value. This difference may stem from the individual effect or the interactions of natural factors such as biophysical, topographic, edaphic and climatic characteristics of the forest, and of factors associated with differences in production methods and means. However, in present-day forestry operations, the estimation of annual wood production levels is performed solely as based on the allowable cut levels, while the effects and interrelations stemming from the factors mentioned above are generally overlooked. For this reason, it is possible to state that current annual production estimations of the annual production in forestry operations are far from being accurate and reliable.

Thus; even if forestry operations follow and analyze market developments very effectively, planning the amount of the raw material wood they will place annually on the market depends solely on using the estimations based on the allowable cut values, which are not compatible with modern business management approaches. Thus, the large error margin in estimates concerning the amount of the raw material wood to be placed annually on the market by forestry operations leads to significant price fluctuations associated with the market demand in terms of units and time. These price fluctuations, in turn, may lead to considerable instability on the market. Furthermore, miscalculating the amount of the product to be produced will also lead to deviations in plans and estimations regarding the storage, stacking, sales bids and annual sales incomes. As a result of this, forestry operations will manage their investments, personnel, machinery-equipment leasing and the procurement of various service types in an unbalanced way, which, in turn, may reduce the profitability of their investments and operations.

In 2012, there were 7,085,545 forest villager in Turkey living in 21,395 forest villages [20]. Forestry activities represent an important source of income for these villagers living in forest villages [21]. Although these villagers also take part in basic forestry activities such as forestation, fire prevention, pest/insect control, production of non-wood forestry products, construction and repair of the forest roads, and the work associated with the production of raw material wood (e.g. cutting, carrying, transporting and stacking), which generally represent the main economic income of the forest villagers [22].

Forest resources have a significantly high per unit employment and income effect. Consequently, the effective and planned use of the forest resources can be helpful in preventing migration from rural areas to urban centers (which is one of the most significant socio-economic problems of the developing countries such as Turkey); in creating employment in rural areas; in creating income-generating activities; in ensuring balance between the labor demand and the labor supply; and in preserving economic stability [23,24].

As described above in general terms; identifying the factors which affect production, as well as the individual and interactive effects of these factors, is one of the main aspects of production planning processes in all types of business operations. In forestry operations, estimating the yield percentage of industrial wood production per unit area with a minimum error margin is of critical importance in the success of the operation, as well as its capability in providing the maximum expected benefit in terms of goods and services.

In this context, numerous scientific estimation methods have been developed. Although these methods are classified in different ways in the literature, they are fundamentally divided into two groups as the quantitative and the qualitative methods [25]. One of the methods used as alternative to traditional estimation methods is the Artificial Neural Network (ANN) [26]. The ANN method has nowadays acquired a broad range of uses in areas such as finance, military, health and various engineering fields [27].

The ANN has previously been used as an estimation method by Atik et al. [28] in meteorological estimation models; by Aydın and Eker [29] in the estimation of river sediment loads; by Alp and Çığızoğlu [30] in determining the relation between precipitation and flow for rivers; by Diler [31] in the estimation modelling of the stock exchange index; by Fırat and Güngör [32] in civil engineering; and by Çuhadar et al. [33] and by Çuhadar and Kayacan [34] in studies assessing tourism demand.

Similarly, estimation and classification studies have been performed using various different ANN techniques by [35-46] in various areas; by [47,48] in financial applications; by [49,50] in educational applications; by [51-53] in transport and telecommunication applications; by [54] in military applications; by [55] in space sciences; and by [56-60] in various industrial applications.

Numerous studies, such as the studies of [61-66], have demonstrated that the ANN can be used as an effective method for determining the relations between snow accumulation, sublimation and closure degree of trees.

The ANN was developed by [67] based on the human brain, and defined as a system consisting of parallel and distributed information processing structures interconnected with one another through weighted connections, and consisting of processors each of which having their own memory. In other words, ANNs are computers programs which imitate biological neural networks, and which can identify unknown and difficult-to-identify relations between the data. Similar to biological neural networks, artificial neural networks are formed by the association of artificial nerve cells, which are also known as the neurons (Fig. 1) [68].

The ANN concept was developed as based on the idea of imitating the brain functioning in digital computers, and the initial studies regarding the ANN focused on mathematically modeling the biological cells (neurons) that constitute the brain [68]. However, ANNs have simpler structures than actual biological neural networks. The prominent feature of these systems is that they consist of a non-algorithmic, fully parallel, adaptable and parallel-distributed memory that is capable of learning [69].

ANNs are non-linear models. Linear models can be advantageous in case they can conceive and clarify important details. However, linear models are not suitable in cases where the relationship at the heart of the relevant problem is fundamentally non-linear [26].

ANNs generally form networks through layers of nerve cells that are arranged in parallel with one another in each layer (Fig. 2). An artificial neural network consists of three layers of interconnected nerve cells, which are the input layer, the output layer, and the hidden layer [32].

Neurons within the network will, depending on the factors affecting the problem, receive one or more inputs, and then provide a number of outputs equal to the number of the expected results from the problem [70].

The process by which ANNs acquire information from known examples/cases in order to gain the ability to make generalizations about unknown examples/cases is referred to as learning. In ANNs, learning involves a process in which initially and randomly assigned weight values are adjusted until a certain required function is fulfilled. ANNs will continue to adjust the weight values as long as they are presented with new examples/cases. The aim of this process is to find the weight values which, based on the examples/cases presented to the network, will produce the correct outputs. Once the network is capable of reaching the correct weight values, this will indicate that it has acquired the capability of making correct generalizations regarding the events which the examples/cases represent [27].

The learning process of artificial neural networks consists of two stages: The first stage involves determining the output provided by the network based on the given example/case. The second stage involves changing the weight of the network connections depending on the accuracy of the output values.

The tests performed following the completion of the training to determine whether the network was able to learn successfully (i.e. its performance) are referred to as the *testing of the network*. The testing is performed by using the examples/cases which were not presented to the network during its learning process. Using the connection weights determined during the learning process, the network will produce outputs for examples/cases it has not encountered before. The accuracy of the obtained outputs will provide information regarding the network's learning status. The example set used for training purposes is referred to as *the training set*, while the set used for testing purposes is referred to as the *test set* [27].

The learning rules used for the training of the ANNs are generally categorized in three groups, which are the supervised learning, the unsupervised learning and the reinforcement learning [71].

When a weight ($W_i$) on the ANN is considered, learning will be mathematically expressed as follows (Equation 1):

$$W_{New}=W_{Old}\pm\Delta W \tag{1}$$

In this Equation, $\Delta W$ provides the amount of correction that will be calculated according to a particular rule and is applied to the relevant weight. The rules used for determining $\Delta W$ are referred to as the learning algorithms, or the learning rules [71].

The architectures of the ANNs can differ from one another with respect to the direction of their connections between the nerves, or the flow direction of signals within the network. As such, there is two main types of network architectures, which are the Feed Forward Network and the Feedback (or Recurrent) Network [27].

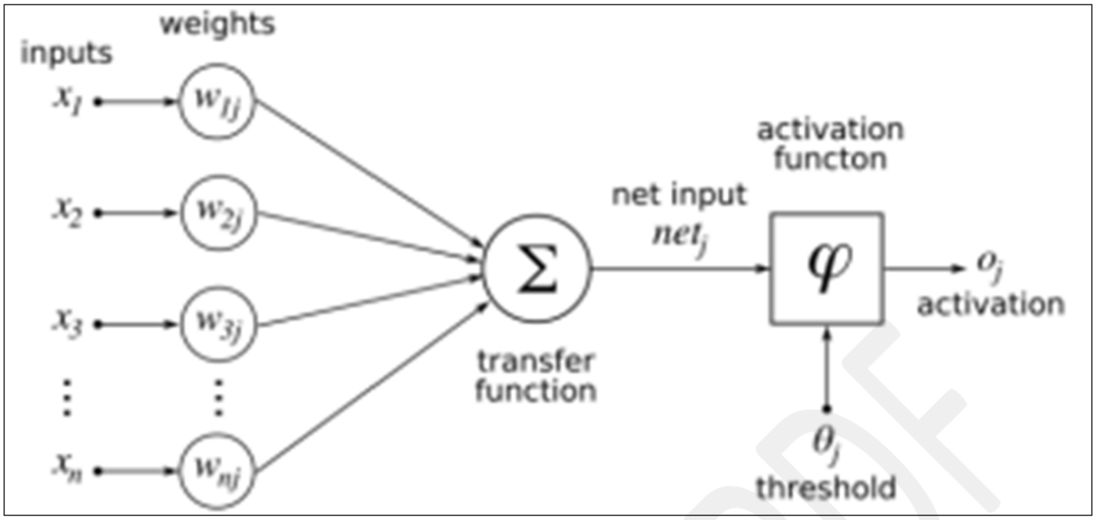


**Fig. 1. An artificial neuron**

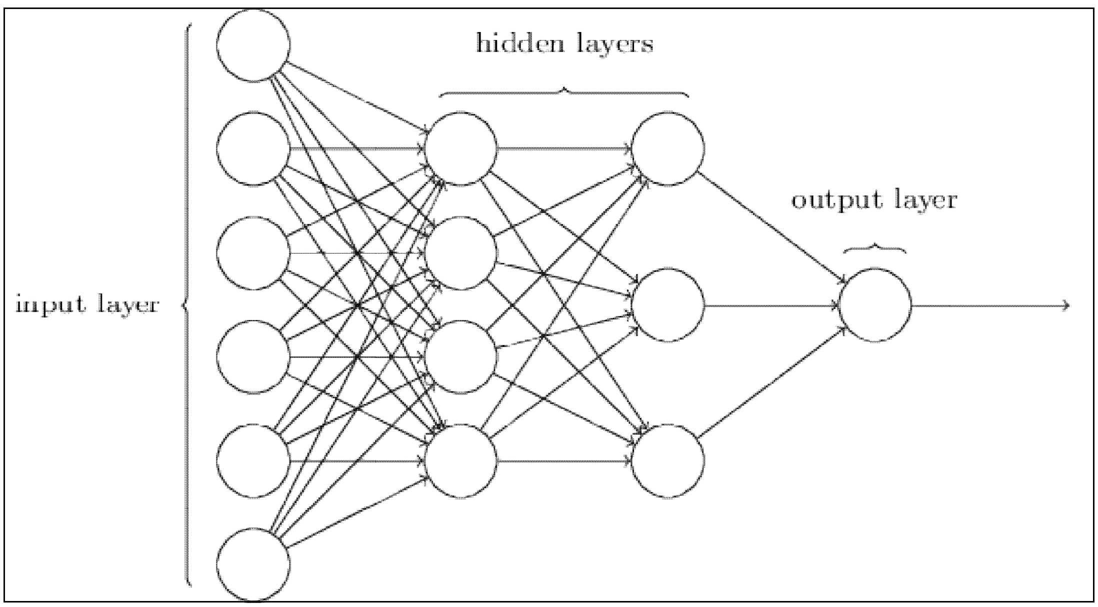


**Fig. 2. An artificial neural network**

In recent years, the ANN has become an extensively studied and implemented method. ANN studies are used in numerous different areas such as classification, optimization, estimation, pattern recognition, modelling and learning [66]. Although the ANNs have a significant potential for widespread use in forestry, the number of the ANN studies that have been performed in this area is somewhat limited [72].

The aim of this study was to estimate the ratio between the industrial wood production per unit area and the allowable cut (the yield percentage per production unit) by using the ANN method. The ANN can then perform appropriate generalizations after learning the non-linear relations between the data through training. Owing to this feature, the ANNs represent an effective method for making estimations. In this context, 26 variables reported by [19] as influencing yield percentage per production unit (and measured on a production unit basis) were used in this study. These variables were organized in 3 main groups, which were the general conditions of the stand, the natural structure of the production unit, and the production methods and tools. The raw data for these variables that constitute the input layer of the ANN were normalized using different normalization techniques. In this study, the Multi-Layer Perceptron (MLP) was used, and, using a feed-forward network architecture and supervised learning techniques, models with 8 neurons and different learning degrees as well as momentum coefficients were formed. These models were then trained by performing trials with different numbers of iterations (100-1000). Following this, all of the developed models were tested using the test data. Following the testing process, the estimated values were compared with the actual values, and the comparisons were performed between the estimation performances of the ANN models with different architectures. By performing numerous trials, we aimed to identify the most effective normalization technique for estimating the yield percentage of the production units, as well as the ANN with the best performance. Based on this, we also attempted to determine the utility of the ANN technique in estimating the industrial wood production yield of forestry operations based on the allowable cut.

## 2. MATERIALS AND METHODS

### 2.1 The Study Area and Data Collection

The study data were collected from 52 production units that were part of the 5-year production program between 2006 and 2010 of the Bartın Province Forestry Operations, Günye Forestry Operation Directorate, located in the Western Black Sea Region of Turkey. The 26 variables constituting the input layer of the ANN are provided in Table 1 along with certain statistical data concerning these variables. The variables were determined from the Operation Management Plan (2001-2010; 2011-2020), production and price lists, and the results of the measurements and the observations performed in this field; these variables were then grouped under 3 main groups, which were the general conditions of the stand, the natural structure of the production unit, and the production methods and tools. The output layer of the ANN model was the industrial wood production percentage of the production units based on the allowable cut.

The Geographical Information System (GIS) was used to obtain relevant data from the 1:25000 scale territory maps and 1:10000 scale management maps through measurements and calculations.

To avoid differences in production that might stem from the working technique and performance of the production workers, attention was paid to the selection of the production units to ensure that the production work was performed by the same production cooperative.

The industrial wood produced in all of the production units were moved to the ramps (the location where the produced wood were loaded onto the transport vehicles) by rolling and/or dragging.

### 2.2 The Application of the Artificial Neural Network Method

In this study, the input layer of the ANN was based on the data for 26 variables obtained from the 52 production units of the Günye Forestry Operation Directorate. The 26 variables in question were described by [19] as affecting the yield of the industrial wood production by productions units. The output layer of the network consisted of the industrial wood production yield of these production units. The industry wood production yield of the units was calculated by using Equation 2.

$$PoY = \frac{Y}{AC}\ x\ 100 \tag{2}$$

*PoY*: Percentage of the industrial wood yield
*Y*: Total amount of the industrial wood obtained from the production unit
*AC*: The allowable cut of the production unit (the total volume of the trees designated for cutting at the production unit).

Data for the 26 variables obtained from the 52 production units were used in the ANN, with 80% of the data (corresponding to the data from 42 production units) being used as training data, while 20% (corresponding to the data from 10 production units) being randomly used as the test data.

**Table 1. Groups, variables, labels, units and some statistics of the variables**

| Group | No | Name of the variable | Label | Unit | Mean | Std. dev. | Scale |
|---|---|---|---|---|---|---|---|
| General conditions of the stand | 1 | Eta per ha (allowable cut) | ALWBH | $m^3$ $ha^{-1}$ | 15.6 | 5.8 | 4.2-32.5 |
| | 2 | Growing stock per ha | GSTCK | $m^3$ $ha^{-1}$ | 214.4 | 58.6 | 91-367 |
| | 3 | Annual volume increment | VOLINC | $m^3$ $ha^{-1}$ | 4.0 | 1.5 | 0.4-7.2 |
| | 4 | Stand height | HEIGHT | m | 30.5 | 2.9 | 25-36 |
| | 5 | Stand site quality degree | SSQUD | - | 2.3 | 0.8 | 1-3 |
| | 6 | Actual number of trees | NTREE | n $ha^{-1}$ | 339.2 | 154.2 | 139-689 |
| | 7 | Actual basal area | BASAR | $m^2$ $ha^{-1}$ | 18.9 | 8.3 | 1.6-36.3 |
| | 8 | Weighed Diameter class | DIAMTR | - | 3.5 | 1.3 | 2-5 |
| | 9 | Density of rhododendron | RHODO | - | 2.7 | 0.9 | 2-4 |
| | 10 | Density of other living cover | OTCVR | - | 1.7 | 0.8 | 1-4 |
| | 11 | Litter cover | LITTR | - | 2.7 | 0.9 | 1-4 |
| | 12 | Stand trunk quality | QUALT | - | 2.3 | 0.9 | 1-4 |
| | 13 | State of abiotic harm in the stand | ABIOT | - | 2.0 | 1.2 | 1-5 |
| Natural structure | 14 | Elevation | ELEV | m | 503.7 | 121.1 | 290-924 |
| | 15 | Slope | SLOP | % | 55.5 | 10.0 | 30-74 |
| | 16 | Aspect | ASPECT | - | 4.7 | 2.2 | 1-8 |
| | 17 | Soil Depth | SDEP | - | 1.9 | 0.3 | 1-2 |
| | 18 | Erosion Level | EROS | - | 2.4 | 0.5 | 1-3 |
| | 19 | Stoniness | STON | - | 1.9 | 0.3 | 1-2 |
| | 20 | Average ground skidding distance | AVSKID | m | 281.7 | 79.5 | 88-575 |
| | 21 | Skidding direction | SKIDIR | - | 1.1 | 0.3 | 1-2 |
| | 22 | Transportation distance | TRNDIS | km | 12.9 | 2.6 | 7.4-18.0 |
| Production methods and tools | 23 | Skidding unit price | SKDPR | $\$ (m^3)^{-1}$ | 16.4 | 4.4 | 5.4-27.9 |
| | 24 | Transportation unit price | TRNPR | $\$ (m^3)^{-1}$ | 10.8 | 2.7 | 2.0-16.7 |
| | 25 | Type of tools used in skidding | TYPTL | - | 1.9 | 0.6 | 1-4 |
| | 26 | Type of tools used in transportation | TRNTL | - | 1.9 | 0.3 | 1-2 |

## 2.3 Normalization of the Data

Many researchers described that, in the Multiple Layer Network (MLN), the normalization of the inputs and outputs closely affects the performance of the network. The literature also describes that the normalization of the data will improve the performance of the Artificial Neural Network [73]. This is because normalization renders the distribution of values within a dataset more orderly. Among the inputs of the ANN, it is possible to have excessively large or small values of different measurement units. When calculating the net inputs, these excessive values may mislead the network by causing extremely large or small values to be generated. In addition, such excessive values may have entered the dataset by accident. Normalizing all inputs with a certain interval (generally between 0 and 1) allows the information from different environments to be examined on the same scale, and the removal of it is associated with erroneously entered very large or small values. A different normalization method may be used for each problem. The designers of MLN can determine their own approach for normalizing the data in hand. Thus, imposing a standard on this subject would not be appropriate [74]. For this reason, the normalization of the data in this study was performed using 2 methods which are among the most commonly used ones in the literature, and which provide positive value outputs. These 2 methods were the Min-Max and the D_Min_Max Normalization methods. The data obtained following the normalization were separated and tested in all of the developed networks.

### 2.3.1 Min-max normalization

This method normalizes the raw data linearly. The *minimum* represents the lowest value a datum can assume, while the *maximum* represents the maximum value it can assume. Data are reduced to a value between 0 and 1 by using Equation 3.

$$\acute{x} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (3)$$

In this Equation;

- $x'$ represents the normalized data.
- $x_i$ represents the input value.
- $x_{min}$ represents the smallest number in the input set.
- $x_{max}$ represents the largest number in the input set.

#### 2.3.2 D min max normalization

In this method, all the data are normalized by being reduced to a value between 0.1 and 0.9 with the aid of Equation 4.

$$\acute{x} = 0.8\text{x}\frac{X_i - X_{min}}{X_{max} - X_{\min}} + 0.1 \quad (4)$$

In this Equation;

- $x'$ represents the normalized data.
- $x_i$ represents the input value.
- $x_{min}$ represents the smallest number in the input set.
- $x_{max}$ represents the largest number in the input set.

### 2.4 Training of the Network

The training of the ANN models was performed using the Multi-Layer Perceptron (MLP), feed-forward network structure. To determine the weights (updated parameters) during the training of the network, errors were allowed to spread from the output layer towards the lower layers, and an algorithm, which optimizes the weighted connections - known as the Backpropagation Algorithm - was used as the training system (Equation 5).

$$e_i = d_i \text{-} y_i(k) \quad (5)$$

- $e_i$ : *i* error sign of the nerve,
- $y_i$ : the output value of the nerve *i* in the output layer of the ANN during iteration number *k* of the training,
- $d_i$ : the desired value for nerve *i*.

The Backpropagation Algorithm was first discovered by [75], and later popularized by Rumelhart et al. [76-77]. This algorithm is the most commonly used method in Artificial Neural Networks [28]. The purpose of the Backpropagation Algorithm is to minimize the suitability function (Equation 3). As the suitability function is dependent of the ANN's weight values, the algorithm involves changing the ANN weights through the most suitable approach.

The suitability function is expressed using the Equation below (Equation 6);

$$E = \frac{1}{2}\sum_i e_i^2(k) = \frac{1}{2}\sum_i (d_i \text{-} y_i(k))^2 \quad (6)$$

One of the important factors which determines the neuron behavior in the ANN is the activation function of the network. This function evaluates the net input arriving to the neuron to determine the corresponding output that will be produced. As is the case with the addition function, various different Equations are used for calculating the output of the activation function [74]. For the neural network, we selected the sigmoid type activation (Equation 7), which requires the neural response to be a continuous function of the inputs, and is recommended for cases where the input values are between 0 and 1. On the other hand, the Levenberg-Marquardt (Trainlm) was used as the training function, while the Mean Squared Error (MSE) was selected as the performance function [68].

$$\Psi(S) = \frac{1}{1 + e^{-s}} \quad (7)$$

By taking into consideration the literature reviews; we tested various networks separately with different architectures (in terms of their number of neurons, iterations, learning degrees and momentum coefficients) according to the two transformation values obtained with the two normalization techniques described above. The estimation values determined through the testing process were compared with the actual values, and the estimation performance of the Artificial Neural Networks with different architectures were compared by taking into account the Mean Absolute Percentage Error (MAPE) values. The network structure with the lowest MAPE value was determined accordingly.

In the literature, the MAPE statistics express the estimation errors in terms of percentages; for this reason, these error values are not meaningful alone, and are hence considered as being superior to other criteria [77]. The statistical expression of the MAPE is provided in Equation 8 [78].

$$\text{MAPE} = \frac{\sum\left|\frac{y_1 - y_2}{y_1}\right|}{n} \text{ x } 100\ (\%) \quad (8)$$

In this Equation;

$y_1$ represents the real values,
$y_2$ represents the estimated values,
$n$: represents the number of the observations.

In this study, the input data of the Artificial Neural Network were obtained using the ArcGIS program, and the data were transferred to a computer environment and normalized using the Microsoft Office Package Program. The Artificial Neural Network method was applied using the Neural Network Toolbox software of the MATLAB R2014a computer program.

## 3. RESULTS AND DISCUSSION

The network we developed in order to estimate the yield percentage of the production units consisted of 1 input layer, 1 intermediate (or hidden) layer and 1 output layer. In the input layer, we utilized the 26 different variables described by [19] as affecting the yield of the industrial wood production in production units. The output of the network was the yield of the industrial wood production at the production units. The multi-layered model formed within the scope of the ANN model used in this study is provided in Fig. 3.

Following the trials performed with the ANN model shown above, an intermediate/hidden layer consisting of 8 neurons was deemed appropriate. It was determined that the training of the network with less than 1000 iterations did not provide satisfactory results. For this reason, trials were performed by setting the number of iterations at 1000 (epoch: 1000), and by using 3 different momentum coefficients (0.6-0.8) with 5 degrees of learning (0.2-0.6). During the training of the network, the data from 42 production units selected randomly from the total of 52 units were employed. The input and output values were normalized using the Min-Max and D_Min_Max normalization techniques, and then presented to the network.

Data from the remaining 10 production units were used for testing the network. Data from the production units used for testing purposes were not included in the network training set. Following this, all of the models were separately tested with the test data as based on the values obtained after the transformations performed with the Min-Max and D_Min_Max normalization techniques. The estimation values obtained based on the testing process were then compared with the actual values, and the estimation performance of the Artificial Neural Networks with different architectures were compared by taking into account the Mean Absolute Percentage Error (MAPE) values. The network structure with the lowest MAPE value was determined accordingly.

Fig. 2 provides the model labels, the parameters and the industrial wood production MAPE values (%) (obtained from 10 production units) for the 8-neuron, multi-layered (MLP) network model developed in this study to estimate the wood production yield percentage.

The input elements of the network consisted of 30 different training sets, with 15 sets for each normalization technique's normalized data. As shown in Table 2, various different network structures and learning degrees were tested in order to obtain the most accurate results. Following this, all of the models were tested using the test data. The estimation values obtained after the test process were compared with one another, and the estimation accuracy of the ANNs with different architectures were evaluated accordingly.

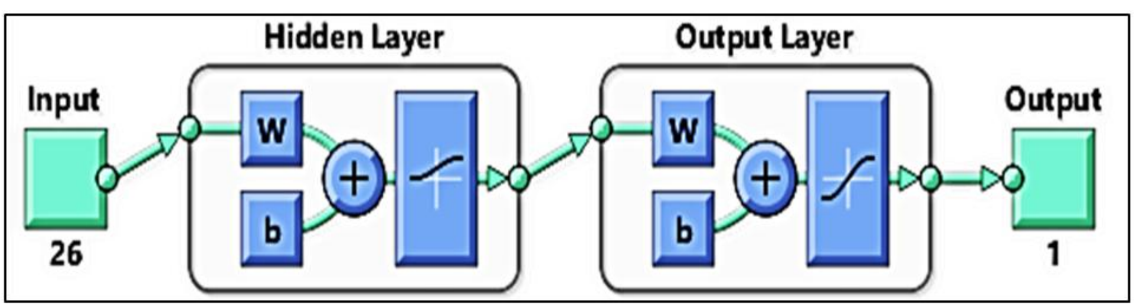


**Fig. 3. The artificial neural network model used during the trials**

**Table 2. Parameter values of the MLP models used for training**

| Label of model | Normalization technique | Degree of learning | Momentum coefficient | MAPE (%) |
|---|---|---|---|---|
| M0206 | Min-Max | 0.2 | 0.6 | 29.3 |
| M0207 | Min-Max | 0.2 | 0.7 | 22.1 |
| M0208 | Min-Max | 0.2 | 0.8 | 20.2 |
| M0306 | Min-Max | 0.3 | 0.6 | 26.4 |
| M0307 | Min-Max | 0.3 | 0.7 | 24.6 |
| M0308 | Min-Max | 0.3 | 0.8 | 23.8 |
| M0406 | Min-Max | 0.4 | 0.6 | 22.4 |
| M0407 | Min-Max | 0.4 | 0.7 | 22.6 |
| M0408 | Min-Max | 0.4 | 0.8 | 21.5 |
| M0506 | Min-Max | 0.5 | 0.6 | 21.0 |
| M0507 | Min-Max | 0.5 | 0.7 | 21.9 |
| M0508 | Min-Max | 0.5 | 0.8 | 21.2 |
| M0606 | Min-Max | 0.6 | 0.6 | 15.5 |
| M0607 | Min-Max | 0.6 | 0.7 | 13.4 |
| M0608 | Min-Max | 0.6 | 0.8 | 16.7 |
| D0206 | D_Min_Max | 0.2 | 0.6 | 10.2 |
| D0207 | D_Min_Max | 0.2 | 0.7 | 17.6 |
| D0208 | D_Min_Max | 0.2 | 0.8 | 9.8 |
| D0306 | D_Min_Max | 0.3 | 0.6 | 15.7 |
| D0307 | D_Min_Max | 0.3 | 0.7 | 22.4 |
| D0308 | D_Min_Max | 0.3 | 0.8 | 14.5 |
| D0406 | D_Min_Max | 0.4 | 0.6 | 13.7 |
| D0407 | D_Min_Max | 0.4 | 0.7 | 8.8 |
| D0408 | D_Min_Max | 0.4 | 0.8 | 5.3 |
| D0506 | D_Min_Max | 0.5 | 0.6 | 7.6 |
| D0507 | D_Min_Max | 0.5 | 0.7 | 12.1 |
| D0508 | D_Min_Max | 0.5 | 0.8 | 10.8 |
| D0606 | D_Min_Max | 0.6 | 0.6 | 11.9 |
| D0607 | D_Min_Max | 0.6 | 0.7 | 21.4 |
| D0608 | D_Min_Max | 0.6 | 0.8 | 14.7 |

Based on the tests performed with the 30 training sets formed according to Table 2, it was determined that the model labeled D0408 with a learning degree of 0.4 and a momentum coefficient of 0.8 provided the most suitable results. The mean MAPE value of the network structures formed using the Min-Max Normalization was 21.5%, while the mean MAPE value of the network structures formed using D_Min_Max Normalization was 21.5%.

In the networks where the Min-Max Normalization technique was used, the lowest MAPE value was determined as 13.4%. This value was obtained with the network labeled M0607, which had a learning degree of 0.6 and a momentum coefficient of 0.7. On the other hand, the highest MAPE value was obtained with the network labeled M0206, which had a learning degree of 0.2 and a momentum coefficient of 0.6. Thus, among the 15 different network structures that used the Min-Max normalization technique, the MAPE values varied between 13.4% and 29.3%.

In networks using the D_Min_Max Normalization technique, the lowest MAPE value of 5.3% was obtained with the network labeled D0408. This MAPE value was also the lowest one obtained among all of the different networks used in our study. The learning degree and momentum coefficient and the D0408 network was 0.4 and 0.8, respectively. On the other hand, among the networks normalized using the D_Min_Max Normalization technique, the highest MAPE ratio (22.4%) was obtained with the network labeled D0397, which had a learning degree of 0.3 and a momentum coefficient of 0.7. Thus, among the 15 different network structures that used the D_Min_Max normalization technique, the MAPE values varied between 5.3% and 22.4%. The lowest MAPE value obtained through the D_Min_Max normalization was 5.3%, while the lowest MAPE value obtained through the Min-

Max normalization was 13.4%. Therefore, an 8.1% difference was observed between the two normalization techniques with respect to the lowest MAPE value they provided. It is thus possible to state that the two different normalization techniques used in this study affected the predictive power of the ANN. The literature described that the normalization of the data has the effect of improving the performance of the Artificial Neural Networks. [79] described that, in the ANN models developed for the classification of diabetes patients, the use of different statistical normalization techniques influenced the performance of the network. [72] previously evaluated the estimations obtained through normalizations for the climatic data of the Adana province, while [80] performed a similar study for the expected *waiting in line period of patients*. Based on the results of these two studies, it was determined the D_Min_Max normalization method provided the results with the highest estimation accuracy and closest to the real values.

In this study, we similarly determined that, in parallel with the information in the literature, the network-generated estimates processed with the D_Min_Max normalization technique provided values that were closer to the real/actual results. Table 3 shows the actual industrial wood production levels/yields for 10 production units together with the production levels/yields estimated using the ANN model labeled D0408 for the same production units. Fig. 4 provides the iteration-dependent error graph for the ANN model labeled D0408.

As shown in this table, the estimated values obtained through the ANN labeled D0408 were fairly close to the actual values. For the 10 production units used for testing purposes (production units 41 to 51), the difference between the ANN estimations and the mean actual yield percentage values was 1.7% (Table 3). The largest difference between the actual values and the ANN estimations (6%) was observed at the production units 46 and 47, while the lowest difference between the actual values and the ANN estimations was observed at the production unit 48 (Fig. 5).

In the measurements performed on the actual and the model-based estimated values for the 10 production units used for testing purposes, the MAPE value was determined as 5.3%. The low MAPE value indicated that the deviations between the actual and the ANN-estimated values regarding the industrial wood production levels was very small. [81] previously classified the estimation models with MAPE values less than 10% as “highly accurate” models, and those with MAPE values between 10% and 20% as “accurate” models. Similarly, Lewis classified models with MAPE values less than 10% as “very good” models; those with MAPE values between 10% and 20% as “good” models; those with MAPE values between 20% and 50% as “acceptable” models; and those with MAPE values above 50% as “inaccurate and wrong” models [82].

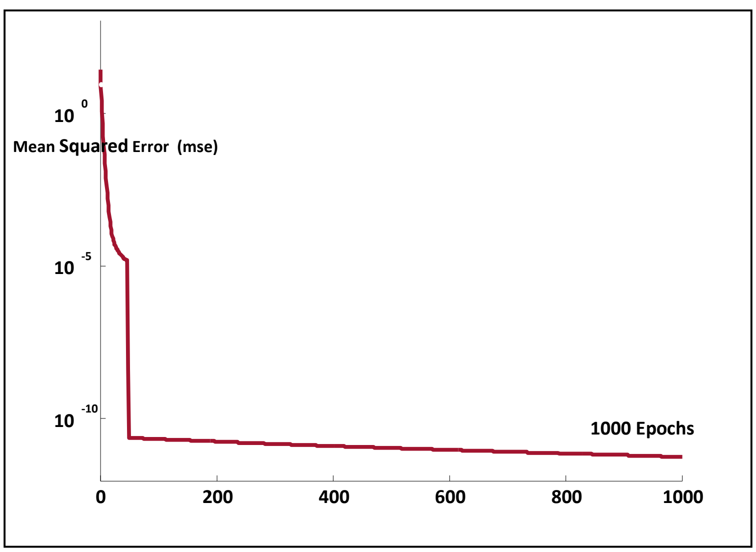


**Fig. 4. The iteration-dependent error graph of an ANN prepared for training**

**Table 3. Values obtained based on the ANN tests**

| Production unit number | Network structure | Industrial wood yield of production units (%) | | MAPE (%) |
|---|---|---|---|---|
| | | Actual value | ANN estimation | |
| 42 | D0408 | 75 | 71 | |
| 43 | | 95 | 90 | |
| 44 | | 91 | 96 | |
| 45 | | 83 | 87 | |
| 46 | | 86 | 78 | |
| 47 | | 88 | 82 | |
| 48 | | 63 | 65 | |
| 49 | | 80 | 77 | |
| 50 | | 78 | 81 | |
| 51 | | 95 | 90 | |
| MEAN | | 83.4 | 81.7 | 5.3 |

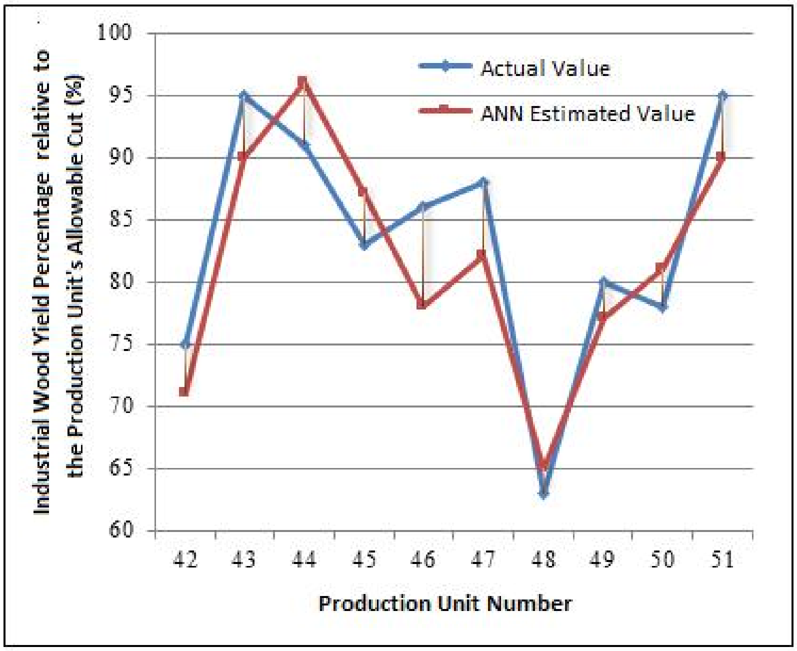


**Fig. 5. Comparison of the actual values with the ANN estimations**

Based on the Witt & Witt's [81] classification method, the ANN model used in this study was - with a MAPE value of 5.3% - determined to be a "highly accurate model." Similarly, according to the classification developed by [82], the model used in this study for determining the industrial wood yield percentage relative to the production unit allowable cut was determined to be a "very good" model.

## 4. CONCLUSIONS

The ever-changing nature of the present-day world requires business operations to initiate and perform changes in all areas from the objectives to the production processes, and from the products to the business organization. To ensure continuity in this environment of constant change, business operations have begun to make extensive use of new approaches and techniques. All these changes and new techniques also affect the planning and control processes of businesses [83]. In forestry operations, the success of the operation is determined by a large variety of individual and multi-dimensional factors that affect the production planning process. In addition to biophysical variables such as the soil and growing stock, the success of a forestry operation is also directly affected by many different economic and social variables such as the demand, the structure of the demand, product prices, the limitations of the operations, socioeconomic conditions, the time value of money, environmental and spatial effects on production, and different production Technologies [84,85].

All forestry operations across the world conduct production activities in a setting that is fully open and exposed to natural conditions. Due to the larger areas as well as the long production periods involved in forestry operation, the organization and structure of these operations differ considerably from those of other types of business operations. Another important feature of forestry operations is the necessity of ensuring the continuity in the management of the operations. In forestry, operation and management plans should be prepared by taking into consideration not only the current demands for goods and services, but also the demands of future generations. The management plans of the State are prepared by considering the yearly allowable cut (or eta) values. Even if the allowable cut values of two production units are the same, the rate of industrial wood material may differ due to geographic features, stand structure and production methods and tools. A production plan based only on the yearly allowable cut values can cause large deviations from production targets by the end of the production period. As a result, an imbalance between the demand and supply may be observed in the industrial wood raw material market [19].

The literature describes numerous scientific estimation methods that are classified according to different approaches. However, due to the characteristics described above that are not applicable for most other types of operations, forestry operations encounter various difficulties in the planning of production per unit time. Nowadays, one method that is being increasingly used in estimation studies as an alternative to traditional estimation methods is the Artificial Neural Network (ANN). The ANN models have already gained a broad range of applications in industrial, military, health and various engineering areas. Although this model has a significant potential for use in forestry, it is possible to observe that the number of ANN studies in forestry remains somewhat limited [66].

In this context, this study attempted to determine the potential utility of the ANNs in determining the level of the industrial wood production relative to the allowable cut in forestry operations. Based on the estimations performed with different ANN models, we were able to determine the model which provided the yield percentage estimations that were closest to the actual values. This multi-layered ANN model with 26 input variables, 8 neurons, 0.4 degree of learning and 0.8 momentum coefficient was able to estimate the industrial wood production yield at the production units of the Günye Forestry Operation Directorate in a close and accurate manner with a MAPE value of only 5.3%. The data from 10 of the production units were also used for testing this model. Based on these tests, it was determined that the mean yield percentage estimations for the production units had only an error ratio of 1.7%, which is a fairly low and acceptable value.

Based on the abovementioned results, we believe that the ANN models have a significant potential for use in the estimation of yield percentage relative to the allowable cut in forestry operations. In conclusion, we can recommend the ANN technique for studies attempting to determine the yield percentages of the production units in forestry operations with different geographical structures, tree types, operation structures, management types, and production tools and methods. This technique will enable forestry operations to perform more accurate and scientific estimations during the planning of industry wood production, and thereby allow these operations to attain a better balance in the areas of production and supply.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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