UNDER PEER REVIEW

Original Research Article

ESTIMATION OF ANNUAL INDUSTRIAL WOOD PRODUCTION LEVEL IN FORESTRY OPERATIONS WITH THE ARTIFICIAL NEURAL NETWORK

Abstract

Numerous estimation methods have been developed to date for estimating the production levels of operations. Although these methods are classified in different ways in the literature, they are fundamentally divided into two groups as quantitative and qualitative methods. In estimation studies, one of the methods used as alternative to traditional estimation methods is the artificial neural network (ANN).

In this study, we attempted to determine the utility of the ANN method in predicting 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, which were 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.

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%, 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 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 (Kobu 1999).

Definitions regarding productions 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 its ability to produce a certain quantity of products that possess suitable quality within a suitable timeframe and at low cost (Saygılı 1991). 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 (Çelikçapa 1999). Özgen (1987) defined production planning as the process of determining beforehand all the necessary means and capabilities, as well as the policies and productions processes which need to be employed, for the products and/or services that are included into the production program.

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

UNDER PEER REVIEW

use of production planning. Owing to production planning, businesses can establish production systems at minimum cost, procure raw materials timely and in desired quantities, and effectively resolve problems relating to the control of production and stock levels (Tekin 2005).

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 (Pearce 1990).

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 (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 materials resources in numerous different branches of industry. Örs & Keskin (2000) 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 mean annual industrial production of roundwood in forests across the world was approximately 1.58 billion m^3 (FAO 2014). 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 roundwood production with an annual mean production of 13.5 million m^3 (Anon. 2007, GDF 2012a).

In Turkey, nearly 99.9% of all forests in Turkey 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 plans' 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 (Eraslan & Eler 2003).

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.

UNDER PEER REVIEW

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 19th 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 supply according to nature (Geray 1989).

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 (Davis & Johnson 1987, OK 1997).

Geray (1992a) considers plans performed 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 operations; neglect the existing social structure; ignore the monetary aspect of the operations, as well as the time value of money; and fail to take into account the level and composition of demand.

Forestry operations, which assume the task of providing society 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 forestry management plans employed by state forestry operations responsible for the preservation and management of forest resources generally ranges 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 years within this period (10-20 years), thus providing the approximate amount of cut/production that is expected for each year (Atik & Yılmaz 2014).

In forestry operations, the amount and variety of 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 the 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 based on 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 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 raw material wood they will place annually on the market solely by using estimations based on the allowable cut values will not be compatible with modern business management approaches. Thus, the large error margin in estimates concerning the amount of raw material wood to be placed annually on the market by forestry operations leads to significant price fluctuations associated with 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 product to be produced will also lead to deviations in forestry operations' plans and estimations regarding storage, stacking, sales bids and annual sales income. As a result of this, forestry operations will manage their investments,

UNDER PEER REVIEW

personnel, machinery-equipment leasing and procurement of various services types in an unbalanced way, which in turn may reduce the profitability of their investments and operations.

As of 2012, there are 7,085,545 forest villager in Turkey living in 21,395 forest villages (GDF 2012b). Forestry activities represent an important source of income for these villagers living in forest villages (Nasırlı 2005). 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 forest roads, work associated with the production of raw material wood (e.g. cutting, carrying, transporting and stacking) generally represents the main economic income of forest villagers (Acar et al. 2001).

Forest resources have a significantly high per unit employment and income effect. Consequently, the effective and planned use of forest resources can assist in preventing migration from rural areas to urban centers (which is one of the most significant socio-economic problems of developing countries such as Turkey); in creating employment in rural areas; in creating income-generating activities; in ensuring balance between labor demand and supply; and in preserving economic stability (Akesen et al. 2002, Geray 1998).

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 operation's success, 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 quantitative and qualitative methods (Frechtling 1996). One of the methods used as alternative to traditional estimation methods is the artificial neural network (ANN) (Zhang et al. 1998). The ANN method has nowadays acquired a broad range of uses in areas such as finance, military, health and various engineering fields (Öztemel 2012).

The ANN has previously been used as an estimation method by Atik et al. (2007) in meteorological estimation models; by Aydın & Eker (2012) in the estimation of river sediment load; by Alp & Çığızoğlu (2004) in determining the relation between precipitation and flow for rivers; by Diler (2003) in the estimation modelling of the stock exchange index; by Furat & Güngör (2004) and by Keleşoğlu & Fırat (2006) in civil engineering; and by Çuhadar et al. (2009) and by Çuhadar & Kayacan (2005) in studies assessing tourism demand.

Similarly, estimation and classification studies have been performed using various different ANN techniques by Udo (1993), Kryzanowski et al. (1993), Balakrishman et al. (1996), Dasgupta et al. (1994), Proctor (1992), Kuan & White (1994), Wilson & Sharda (1994), Fletcher & Goss (1993), Coats & Fant (1991), Altman et al. (1994), Salchenberger et al. (1992), and Tam & Kiang (1992) in various areas; by Hardgrave et al. (1994), and Gorr et al. (1994) in financial applications; by Palocsay et al. (1996), and Wang (1994) in educational applications; by Zhang & Thomopoulos (1989), Collins & Evans (1994), and Nygard et al. (1990) in transport and telecommunication applications; by Wacholder (1989) in military applications; by Johnston & Adorf (1992) in space sciences; and by Burke & Rangwala (1991), Kaparthi & Suresh (1994), Madey et al. (1992), Romano et al. (1989), and Sunil et al. (1990) in various industrial applications.

Numerous studies, such as the studies of Coughlan & Running (1997), Hedstorm & Pomeroy (1998), Murray & Buttle (2003), Lundberg et al. (2004), Suzuki et al. (2008) and Aydın & Duyar (2009), have demonstrated that the ANN can be used as an effective method for

UNDER PEER REVIEW

determining the relations between snow accumulation, sublimation and closure degree of trees.

The ANN was developed by Elmas (2003) 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 that each have 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, also known as neurons (Figure 1) (Efe & Kaynak 2000).

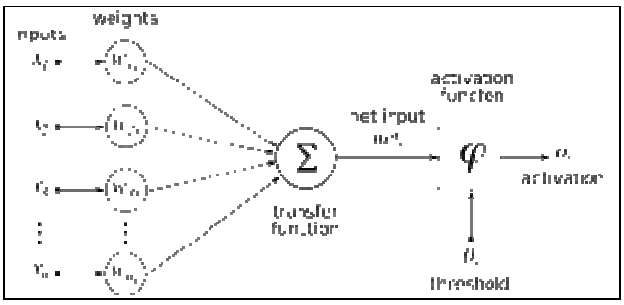

Figure 1. An artificial neuron.

The ANN concept was developed based on the idea of imitating the brain's functioning on digital computers, and the initial studies regarding the ANN have focused on mathematically modeling the biological cells (neurons) that constitute the brain (Efe & Kaynak 2000). 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 (Özbay 1999).

ANNs are non-linear models. Linear models can be advantageous in case they can understand and clarify important details. However, linear models are not suitable in cases where the relationship at the heart of relevant problem is fundamentally non-linear (Zhang et al. 1998).

ANNs generally form networks through layers of nerve cells that are arranged in parallel with one another in each layer (Figure 2). An artificial neural network consists of three layers of interconnected nerve cells, which are the input layer, output layer, and hidden layer (Fırat & Güngör 2004).

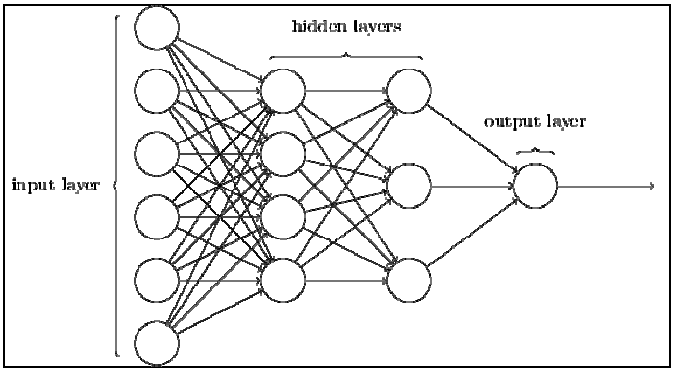

Figure 2. An artificial neural network.

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 expected results from the problem (Yıldız 2001).

UNDER PEER REVIEW

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 (Öztemel 2012).

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 training to determine whether the network was able to learn successfully (i.e. its performance) are referred to as the testing of the network. Testing is performed by using 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 (Öztemel 2012).

The learning rules used for the training of ANNs are generally categorized into three groups, which are supervised learning, unsupervised learning and reinforcement learning (Çuhadar 2006).

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

$$W_{New}=W_{Old}\pm\Delta W \qquad \text{Formula 1}$$

In this formula, ΔW provides the amount of correction that will be calculated according to a particular rule and applied to the relevant weight. The rules used for determining ΔW are referred to as the learning algorithms, or learning rules (Çuhadar 2006).

The architectures of ANNs can differ from one another with respect to the direction of their connections between 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 (Öztemel 2012).

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 (Yavuz & Deveci 2012). Although ANNs have a significant potential for widespread use in forestry, the number of ANN studies that have been performed to date in this area is somewhat limited (Aydın & Duyar 2009).

The aim of this study was to estimate the ratio between industrial wood production per unit area and allowable cut (the yield percentage per production unit) by using the ANN method. ANN can then perform appropriate generalizations after learning the non-linear relations between the data through training. Owing to this feature, ANNs represent effective method for making estimations. In this context, 26 variables reported by Atik & Yılmaz (2014) 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

UNDER PEER REVIEW

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 feedforward 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 test data. Following the testing process, estimated values were compared with actual values, and 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 Operation's 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 measurements and 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 during the selection of production units to ensuring 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) rolling and/or dragging.

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

Group	No	Name of variable	Label	Unit	Mean	Std. Dev.	Scale
General conditions of 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

UNDER PEER REVIEW

	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

2.2. The Application of the Artificial Neural Network Method

In this study, the input layer of the ANN was based on data for 26 variables obtained from the 52 production units of the Günye Forestry Operation Directorate. The 26 variables in question were described by Atik & Yılmaz (2014) as affecting the yield of 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 using Formula 2.

$$PoY = \frac{Y}{AC}\ x\ 100 \qquad \text{Formula 2}$$

PoY: Percentage of industrial wood yield
Y: Total amount of 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 data from 42 production units) being used as training data, while 20% (corresponding to data from 10 production units) being randomly used as test data

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 (Masters 1993). This is because normalization renders the distribution of values within a data set more orderly. Among the inputs of the ANN, it is possible to have excessively large or small values of different measurement units. When calculating 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 data set by accident. Normalizing all inputs with a certain interval (generally between 0 and 1) allows information from different environments to be examined on the same scale, and the removal of effects associated with erroneously entered very large or small values. A different

UNDER PEER REVIEW

normalization method may be used for each problem. The designers of an MLN can determine their own approach for normalizing the data in hand. Thus, imposing a standard on this subject would not be appropriate (Öztemel 2003). 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 both provide positive value outputs. These 2 methods were the Min-Max and the D_Min_Max Normalization methods. The data obtained following normalization were separated tested in all of the developed networks.

2.3.1. Min-Max Normalization

This method normalizes 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 Formula 3.

$$\acute{x} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad \text{Formula 3}$$

In this formula;

x' represents 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 data are normalized by being reduced to a value between 0.1 and 0.9 with the aid of Formula 4.

$$\acute{x} = 0.8\text{x}\frac{X_i - X_{min}}{X_{max} - X_{min}} + 0.1 \qquad \text{Formula 4}$$

In this formula;

x' represents 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. Training of the Network

The training of the ANN models was performed using the Multi-Layer Perceptron (MLP), feedforward network structure. To determine the weights (update the 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 weighted connections – known as the Backpropagation algorithm – was used as the training system (Formula 5).

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

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,

UNDER PEER REVIEW

d_i: the desired value for nerve i.

The backpropagation algorithm was first independently discovered by Werbos (1977), and later popularized by Rumelhart et al. (1986). This algorithm is the most commonly used method in artificial neural networks (Atik et al. 2007). The purpose of the backpropagation algorithm is to minimize the suitability function (Formula 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 formula below (Formula 6);

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

One of the important factors which determines 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 formulae are used for calculating the output of the activation function (Öztemel 2003). For the neural network, we selected the sigmoid type activation (Formula 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 (Efe & Kaynak 2000).

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

By taking into consideration the literature reviews we performed; we separately tested various networks with different architectures (in terms of their number of neurons, iterations, learning degree and momentum coefficient) 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, MAPE statistics express estimation errors in terms of percentages; for this reason, these error values are not meaningful in themselves, and are hence considered as being superior to other criteria (Akgül 2011). The statistical expression of the MAPE is provided in Formula 8 (Cho 2003).

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

In this formula;
y_1 represents real values,
y_2 represents estimated values,
n: represents the number of observations.

In this study, the input data of artificial neural network were obtained using the ArcGIS program, while the data were transferred to a computer environment and normalized using

UNDER PEER REVIEW

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 Atik & Yılmaz (2014) as affecting the yield of industrial wood production in production units. The output of the network was the yield of 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 Figure 3.

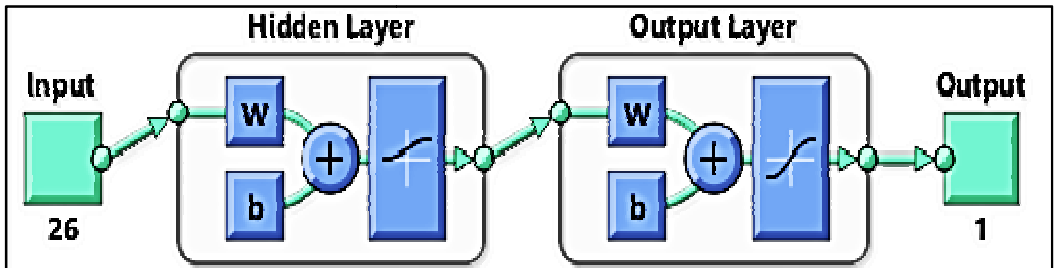

Figure 3. The artificial neural network model used during the trials

Following trials performed with the ANN model shown above, an intermediate/hidden layer consisting of 8 neurons was deemed appropriate. It was determined 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, data from 42 production units selected randomly from the total of 52 units were employed. 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 unit were used for testing the network. Data from the productions units used for testing purposes were not included into the network's training set. Following this, all of the models were separately tested with the test data, based on the values obtained following 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.

Figure 2 provides the model labels, parameters and 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 wood production yield percentage.

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

UNDER PEER REVIEW

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

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 following the test process were compared with one another, and the estimation accuracy of the ANNs with different architectures were evaluated accordingly.

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 Min-Max Normalization and 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 values 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, 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 30 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, 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

UNDER PEER REVIEW

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 (Masters 1993). Jayalakshmi & Santhakumaran (2011) described that, in ANN models developed for the classification of diabetes patients, the use of different statistical normalization techniques influenced the performance of the network. Yavuz & Deveci (2012) previously evaluated the estimations obtained through normalizations for the climatic data of the Adana province, while Deveci (2012) 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 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, 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. Figure 4 provides the iteration-dependent error graph for the ANN model labeled D0408.

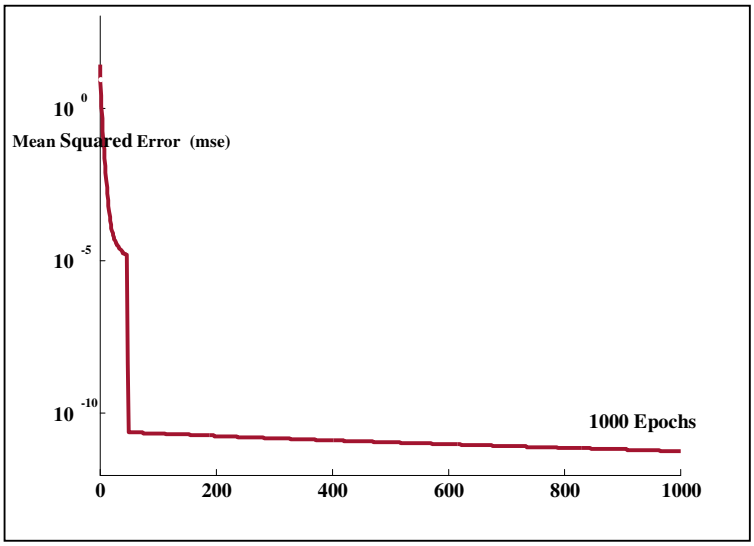

Figure 4. The iteration-dependent error graph of an ANN prepared for training.

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	

UNDER PEER REVIEW

MEAN	83.4	81.7	5.3

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 actual values and ANN estimations (6%) was observed at production units 46 and 47, while the lowest difference between actual values and ANN estimations was observed at production unit 48 (Figure 5).

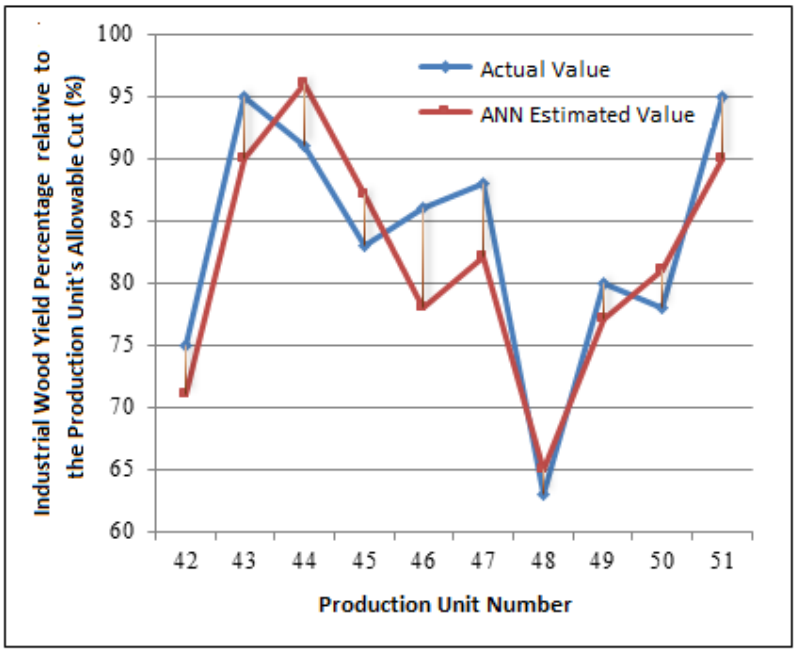

Figure 5. Comparison of actual values with ANN estimations.

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. Witt & Witt (1992) previously classified estimations 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 (Lewis 1982).

Based on the Witt & Witt's (1992) 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 Lewis (1982), the model used in this study for determining the industrial wood yield percentage relative to the production unit's 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 their objectives to their production processes, and from their products to their business organization. To ensure continuity in this environment of

UNDER PEER REVIEW

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 (Öztürk 2001). 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 demand, the structure of demand, product prices, the limitations of the operation, socioeconomic conditions, the time value of money, environmental and spatial effects on production, and different production technologies (Geray 1992b).

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 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 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 yearly allowable cut values can cause large deviations from production targets by the end of production period. As a result, an imbalance of demand to supply may be observed in the industrial wood raw material market (Atik & Yılmaz 2014).

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 estimations studies as an alternative to traditional estimation methods is the artificial neural network (ANN). 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 (Aydın & Duyar 2009).

In this context, this study attempted to determine the ANN's potential utility in determining the level of industry wood production relative to the allowable cut in forestry operations. Based on estimations performed with different ANN models, we were able to determine the model which provided 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 industrial wood production yield at the production units of the Günye Forestry Operation Directorate fairly closely and accurately, with a MAPE value of only 5.3%. 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 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 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

UNDER PEER REVIEW

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.

References

Acar H.H., Eker M., Topalak Ö., 2001. Ergonomic Approaches and Association at Work in the Forest, 8. National Ergonomics Congress, Proceedings, pp. 318-324, İzmir.

Akesen A., Ekizoğlu A., Yurdakul S., 2002. Problems of the forest village development cooperative and solutions, First National Forestry Cooperatives Symposium, pp. 84, Kastamonu.

Akgül I., 2011. Time Series Analysis and ARIMA models. Der Publications, İstanbul, 251 p.

Alp M., Cığızoğlu H.K., 2004. Modelling rainfall-runoff relation using different artificial neural network methods. ITU Journal of Engineering, 3(1):80-88.

Altman E.I., Marco G., Varetto F., 1994. Corporate distress diagnosis: Comparasions using linear discriminant analysis and neural networks (the Italian experience). J. of Banking and Finance, 18(3):505-529.

Anonymous, 2001. Report of forestry special expertise commission in the preparation of 8th five – year development plan. 539 p.

Anonymous, 2007. Report of forestry special expertise commission in the preparation of ninth five – year development plan. 102 p.

Atik A., Yılmaz B., 2014. Factors affecting industrial wood material production yield in Turkey's natural beech Forest. Annals of Forest Research, 57(1):149-162.

Atik K., Deniz E., Yıldız E., 2007. Modeling meteorological data by artificial neural network. KSU Journal of Science and Engineering, 10(1):148-152.

Aydın A., Duyar A., 2009. Snow accumulation prediction in forests using artificial neural networks. Journal of the Bartın Faculty of Forestry 1 (Special Issue):117-125.

Aydın A., Eker R., 2012. Prediction of daily suspended sediment load using radial basis function neural networks. Ormancılık Dergisi 8(2):36-44.

Balakrishman P.V., Cooper M., Jacob V.S., Lewis P.A., 1996. Comparative performance of the FSCL neural net and k-means algorithm for market segmentation. European Journal of Operational Research, 93(2):346-357.

Burke L.L., Rangwala S., 1991. Tool condition monitoring in metal cutting: A neural network approach. Journal of Intelligent Manufacturing, 2(5):269-280.

Cho V., 2003. A comparison of three different approaches tor tourist arrival forecasting. Tourism Management, 24(3):323-330.

Coats P.K., Fant L.F., 1991. A neural network approach to forecasting financial distress. Journal of Business Forecasting, 10(4):9-12.

Collins A., Evans A., 1994. Aircraft noise and residential property values. Journal of Transport Economics and Policy, 28(2):175-197.

Coughlan J.C., Running S.W., 1997. Regional ecosystem simulation: A general model for simulating snow accumulation and melt in mountainous terrain. Landscape Ecology, 12:119-136.

UNDER PEER REVIEW

Çelikçapa F.O., 1999. Planning of production, Alfa Publications, ISBN 975-316-218-9, p. 11, İstanbul.

Çuhadar M., 2006. Forecasting tourism demand by artificial neural networks and time series methods (a comparative analysis in inbound tourism demand to Antalya). Süleyman Demirel University, Department of Business Administration, Unpublishing Ph.D. Thesis, Isparta, 174 p.

Çuhadar M., Güngör, İ., Göksu A., 2009. Forecasting tourism demand by artificial neural networks and time series methods: a comparative analysis in inbound tourism demand to Antalya. Suleyman Demirel University the Journal of Faculty of Economics and Administrative Sciences, 14(1):99-114.

Çuhadar M., Kayacan C., 2005. Occupancy Rate Forecasting in Lodging Properties by Using Artificial Neural Networks: An Experimental Study of Lodging Properties in Turkey. Anatolia: Journal Tourism Research, 16(1):24-30.

Dasgupta C.G., Dispensa G.S., Ghose S., 1994. Comparing the predictive performance of a neural network model with some traditional market response models. International Journal of Forecasting, 10(2):235-244.

Davis L., Johnson K.N., 1987. Forest management, Third edition, McGraw-Hill Inc., ISBN: 0-07-032625-8, pp. 554, USA.

Deveci M., 2012. Using artificial neural networks and using them to estimate of standby time. Unpublishing Thesis, Ankara, 101 p.

Diler A.İ., 2003. Forecasting the Istanbul Stock Exchange National 100 Index Using an Artificial Neural Network. Journal of IMKB, 7(25-26): 66-81.

Efe Ö., Kaynak O., 2000. Artificial Neural Networks and Applications, Boğaziçi University, İstanbul, pp. 6.

Elmas Ç., 2003. Artificial Neural Networks (Theory of Architecture, Education, Practice), Seçkin Publishing, Ankara, pp. 23.

Eraslan İ., Eler Ü., 2003. Planning and control of the forest management, Publisging of Süleyman Demirel University, No: 35, ISBN 975-7929-64-6, pp. 2, Isparta.

Fırat M, Güngör M., 2004. Determination of carried suspended sediment concentration and amount by artificial neural networks. IMO Technical Journal, 2004: 3267-3282.

Fletcher D., Goss E., 1993. Forecasting with neural networks: An application using bankruptcy data. Information and Management, 24(3):159-167.

Frechtling D., 1996. Practical Tourism Forecasting, Oxford: Butterworth-Heinemann, pp.7.

Food and Agriculture Organization of the United Nations (FAO), 2011. http://faostat.fao.org (access date: 14.11.2014).

General Directorate of Forestry (GDF), 2012a. Strategic plan. General Directorate of Forestry Press, Ankara, 82 p.

General Directorate of Forestry (GDF), 2012b. Forestry statistics 2012. General Directorate of Forestry Press, Ankara, 162 p.

Geray U., 1989. Contemporary frame of the forestry, Journal of İstanbul University Faculty of Forestry, 39(4):17-27.

UNDER PEER REVIEW

Geray U., 1992a. Critical of forest management plans and new approaches, Proceeding, Ministry of Forestry, Ankara, pp. 201.

Geray U., 1992b. Production planning in forest management. Unpublishing Lesson Texts 1, İstanbul, pp. 8.

Geray U., 1998. Management of Forest Resources, the National Environmental Action Plan, DPT Publishing, ISBN 975-19-1917-7, Ankara, 115 p.

Geray U., Türker A., Yılmaz E., 2001. Functional (functional) a different approach to planning, Journal of Forest Engineering, 38(3):19-23.

Gorr W.L., Nagin D., Szczypula J., 1994. Comparative study of artificial neural network and statistical models for predicting student grade point averages. International Journal of Forecasting, 10(19:17-34.

Hardgrave B.C., Wilson R.L., Walstrom K.A., 1994. Predicting graduate student success: A comparison of neural networks and traditional techniques. Computers and Operations Research, 21(3):249-263.

Hedstorm N.R., Pomeroy J.W., 1998. Measurements and modelling of snow interception in the boreal forest. Hydrological Processes, 12:1611-1625.

Jayalakshmi T., Santhakumaran A., 2011. Statistical Normalization and Back Propagation for Classification. International Journal of Computer Theory and Engineering, 3(1):89-93.

Johnston M.D., Adorf H.M., 1992. Scheduling with neural networks: The case of the Hubble Space Telescope. Computers and Operations Research, 19(3, 4):209-240.

Kaparthi S., Suresh N.C., 1994. Performance of selected part-machine grouping techniques for data sets of wide ranging sizes and imperfection. Decision Sciences, 25(4):515-539.

Kobu B., 1999. Production Management, İstanbul University Publishing, No: 04, p. 2, İstanbul.

Kryzanowski L., Galler, M., Wright D.W., 1993. Using artificial neural network to pick stocks. Financial Analysis Journal, 49(4):21-27.

Kuan C.M., White H., 1994. Artificial neural networks: An econometric perspective. Econometric Reviews, 13(1):1-91.

Madey G.R., Weinroth J., Shah V., 1992. Integration of neurocomputing and system simulation for modelling continuous improvement systems in manufacturing. Journal of Intelligent Manufacturing, 3:193-204.

Masters T., 1993. Practical neural network recipes in C^{++}. Academic Press. Inc., San Diego CA., pp. 1-12.

Murray C.D., Buttle J.M., 2003. Impacts of clear-cut harvesting on snow accumulation and melt in a northern hardwood forest. Journal of Hydrology, 271:197-212.

Lewis C.D., 1982. Industrial and business forecasting methods. London: Butterworths Publishing, pp. 509.

Lundberg A., Nakai Y., Thunehed H., Halldin S., 2004. Snow accumulation in forests from ground and remote-sensing data. Hydrological Processes, 18:1941-1955.

Nasırlı C., 2005. Our forestry and relationship village with forest, Forest and Hunt, 2005(2):26-34.

UNDER PEER REVIEW

Nygard K.E., Juell P., Kadaba N., 1990. Neural networks for automated vehicle routing heuristics. ORSA Journal of Computing, 2(4):353-364.

Ok K., 1997. Economic analysis of cutting layout in same old forest, Unpublished PhD Thesis, İstanbul University, pp. 4, İstanbul.

Örs Y., Keskin H., 2000. Wood material knowledge. Gazi University. 2000:352. 183 p.

Özbay Y., 1999. Instant Recognition of ECG Arrhythmias, PhD Thesis, Konya, pp. 10-15.

Özgen H., 1987. Management of the production, Bizim Büro Publishing, Ankara, p. 150.

Öztemel E., 2012. Artificial neural networks, Papatya Publishing, İstanbul, 232 p.

Öztemel E., 2003, Artificial neural networks, The first edition, İstanbul: Papatya Publishing, 232 p.

Öztürk A., 2001. Operationsr, Genişletilmiş, Ekin Publishing, Bursa.

Pearce P.H., 1990. Introduction of Forestry Economics, University of British Colombia Press, Vancouver, 398 p.

Polocsay S.W., Stevens S.P., Brookshire R.G., Sacco W.J., Copes W.S., Buckman R.F., Smith J.S., 1996. Using neural networks for trauma outcome evaluation. European Journal of Operational Research, 93:369-386.

Proctor R.A., 1992. Marketing decision support systems: A role for neural networks. Marketing Intelligence and Planning, 10(1):21-26.

Romano R., Maimon O., Furst M., 1989. Neural net implementation for assigning a product to a production line. In Proceeding of the IEEE International Joint Conference on Neural Networks, Washington D.C., Vol. 2, pp. 577.

Rumelhart D.E., Hinton G.E., Williams R.J., 1986 Learning internal represantation by back-propagating errors. In: Rumelhart D.E., McCleland J.L., The PDP Research Group, Paralel Distributed Processing: Explorations in the Microstructure of Cognition, MIT Press, MA.

Salchenberger L.M., Cinar E.M., Lash N.A., 1992. Neural networks: A new tool for predicting thrift failures. Decision Sciences, 23(4):899-916.

Saygılı I., 1991. Functions of production management, İstanbul University Publishing, No: 244, p. 3, İstanbul.

Sunil E.V.T., Shin Y.C., Kumara S.R.T., 1990. Machining condition monitoring via neural networks. In monitoring and Control of Manufacturing Processes, eds. S. Y. Liang and T. Tsolo, ASME Press, Fairfield, NJ, pp. 85-95.

Suzuki K., Kodama Y., Yamazaki T., Kosugi K., 2008. Snow accumulation on evergreen need leaved and deciduous broad leaved trees. Boreal Environment Research, 13:403-416.

Tam K.Y., Kiang M.Y., 1992. Managerial applications of neural networks: The case of bank failure predictions. Management Sciences, 38(7):926-947.

Tekin M., 2005. Management of the production (Volume I), ISBN 975-95135-2-8, p. 266, Konya.

Udo G., 1993. Neural network performance on the bankruptcy classification problem. Computers and Industrial Engineering, 25(4):377-380.

Wacholder E., 1989. A neural network based optimization algorithm for the static weapon target assignment problem. ORSA Journal of Computing, 1(4):232-246.

UNDER PEER REVIEW

Wang S., 1994. Neural networks for monotonic nonlinear models. Computers and Operations Research, 21(2):143-154.

Werbos P.J., 1977. Advanced forecasting methods for global crisis warning and models of intelligence. General Systems Yearbook, 22:25-38.

Wilson R.L., Sharda R., 1994. Bankruptcy prediction using neural networks. Decision Support Systems, 11(5):545-557.

Witt S.F., Witt C.A., 1992. Modelling and forecasting demand in tourism. Londra: Academic Press.

Yavuz S., Deveci M., 2012. The effect of statistical normalization techniques on the performance of artificial neural network. Journal of Erciyes University, 40:167-187.

Yıldız B., 2001. Artificial neural network usage to prediction of financial failure and an empirical application in public company, Journal of IMKB, 17, pp. 54.

Zhang G., Patuwo, G.E., Hu, M.Y., 1998. Forecasting with Artificial Neural Networks: The State of The Arts. International Journal of Forecasting, 4(1):35-62.

Zhang L., Thomopoulos S.C.A., 1989. Neural network implementation of shortest path algorithm for traffic routing in communication networks. In proceeding of the IEEE International Joint Conference on Neural Networks, Washington D.C., Vol. 2, pp. 591.