A COMPARATIVE STUDY OF ARTIFICIAL NEURAL NETWORKS AND MULTIPLE REGRESSION ANALYSIS FOR MODELING SKIDDING TIME

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Abstract. One of the most important functions of forests is providing raw material for wood. Timber extraction is among the most technically demanding, expensive and time consuming activities for wood raw material production. The analysis of timber extraction activities is complex and it is quite difficult to model them. Therefore, Artificial Neural Networks (ANN) frequently used as a modelling tool in the analysis of complex problems have been used to solve this issue. The aim of this study is to investigate the feasibility of ANN's including Multilayer Perceptron (MLP), Cascade Forward Back Propagation (CFBP) and compare the predictions for total time during log skidding operations stations in Eastern Black sea region (Giresun Forest District Directorates) of Turkey with those of the Multiple Regression Analysis (MRA). Moreover, standard times are calculated, and affective factors are determined, after which the effectiveness levels are evaluated at each working stage by way of timing determinations when skidder is used for timber extraction. The comparison of models were carried out by using the correlation coefficient, mean squared error, root mean square errors and mean absolute error. The comparison results indicate that MLP and CFBP models are better at predicting the total time during log skidding operations in comparison with the MRA model. These results have put forth that artificial neural networks have a greater prediction in comparison with multiple regression analysis for predicting the skidding time in timber extraction operations and that less erroneous results are obtained. It is observed that artificial neural networks can be preferred in cases for which the multiple regression analysis predictions have not been met and the analysis cannot be performed.
Keywords: *timber extraction, log skidding, multilayer perceptron, cascade forward back propagation, Turkey*

Introduction

Turkey has a total of 22.7 million hectares of forest area, which makes up 27% of its total land area. Almost 46% of the total area is on steep land with slopes greater than 40%. Thus, harvesting in mountainous regions has always played a significant role (GDF, 2017). Forestry operations in Turkey are carried out under different conditions on a forest area of approximately 22.7 million hectares, located at different parts of the country (Çalışkan et al., 2017).

Timber harvesting, as a succession of interrelated and interdependent operations in timber production, felling, processing and timber transport. Timber transport consists of two sub phases: timber extraction and further transport that are mutually dependent (Bayoğlu, 1962; Seçkin, 1978; FAO, 1982; Erdaş, 1986; Haarlaa and Jurvelius, 1987; Acar, 1994; Dykstra and Heinrich, 1996; Heinimann, 1999; Karaman, 2001; Heinimann and Stampfer, 2003; Pentek, 2008; Çalışkan et al., 2017).

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Different tools and methods are used according to technical, economic and environmental factors for timber extraction operations which is one of the stages of wood raw material production. Skidding the wood raw material on skid trails via forest tractors or agricultural tractors to place on temporary stacking locations (ramp) is one of these methods. Land topography is among the most distinctive factors in skidding work. Timber extraction methods are generally determined according to ground slope classes. The slope groups taken as basis for determining production type are as follows: using agricultural tractor and animals for skidding 0-33% ground slope, using skidder (MB Trac 900) for cable drawing 34-50% ground slope and cable timber extraction 50%< ground slope (Erdas et al., 1986; Heinimann, 1999). Timber extraction is the most difficult and expensive stages of producing wood raw material and also has the highest environmental damage. A planned approach is required for shortening this process, making the work easier, improving efficiency and thus attaining an economical process (Marchi et al., 2014).

When wood raw material skidding activities are taken into consideration with a system approach, there is a necessity for determining the standard times for different conditions that can be used while planning, applying and inspecting skidding activities which will also form a basis to ensure that skidding workers receive equal pay under equal conditions. Effectiveness of operating conditions while calculating standard time is quite high especially for mountainous forests. Determining the wages according to these factors is of vital importance for ensuring wage justice among employees and for the cost effectiveness of forest management for employers. There are various studies on timber extraction operations in which time studies have been carried out for cable drawing via agricultural tractors and forest tractors (Acar, 1995, 1997; Karaman, 1997; Öztürk, 2005; Tunay et al., 2002; Öztürk, 2010; Çağlar, 2016).

ANN is used as a popular method in different engineering applications by many researchers. ANNs are software designed for simulating the operation of simple biological neural systems (Yurtoğlu, 2006). The main reason why a human being may develop solutions for issues that require thinking and observation skills is his/her ability to learn through experience (Sağıroğlu et al., 2003). Therefore, ANN may be a beneficial tool in engineering applications (Topçu and Sarıdemir, 2008). ANN is a strong tool especially for data models with low regression coefficients (Esteban et al., 2009). ANN's are used for modelling complex operations in many engineering fields ranging from aeronautics, electronic, production, robotics, communication, construction, forest etc.

ANN's was successfully implemented in the field of forest modelling. Particularly, ANN approach has been used for many objectives modeling individual tree survival probabilities (Guan and Gertner, 1991), forest age using TM images (Jensen et al., 1999), tree mortality (Hasenauer et al., 2001; Castro et al., 2013), forecasting of industrial wood demand (Güngör et al., 2004), pine bark volume (Diamantopoulou, 2005), tree volume (Diamantopoulou, 2005a; Diamantopoulou and Milios, 2010; Özçelik et al., 2008, 2010), tree stem diameters (Diamantopoulou, 2005b; Leite et al., 2011), tree felling times (Karaman and Çalışkan, 2009), tree heights (Diamantopoulou and Özçelik, 2012; Özçelik et al., 2013), diameter distributions (Cai et al., 2012) predict of skidding time (Naghdi and Ghajar, 2012), trunk volume estimates (Bayati and Najafi, 2013), prediction of cable drawing time (Bayati and Najafi, 2015), tree diameter increments (Ercanlı et al., 2016), describing diameter distribution (Bolat et al., 2016), bark volume estimation (Çatal et al., 2018).

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The use of artificial neural networks in timber extraction is at a starting stage in Turkey. Hence, there are a few studies in forestry literature which compare the performance of artificial neural networks with other models. For this reason, the aim of this study was to investigate the feasibility of two different reputed types of ANN's and compare the results with those of MRA for predicting the total time during log skidding operations stations. Thus, the network architecture, training algorithm and transfer function that yielded the best result were determined. The data set was separated into three sets as training, test and validation. The training data set used for the training of ANN which makes up the majority of the input data set is used to maximize the ability of the network to predict the correct results and the minimize the error. Test data set is not considered during learning and is used to test the success rate for the prediction of the network after the learning stage. Control data set used during the training of the network. If the performance of the trained data set is very low, but the performance of the control set is high; this raises a suspicion that the network has memorized. In such cases, the network has to be trained again (Çelik, 2004).

Material and Methods

Study Area

This study was carried out at the Anbardağ forest planning unit covering an area of approximately 5975.0 ha in the Giresun province in the north-eastern Black Sea region of Turkey. The area is located between 40° 42' 47" – 40° 30' 13" North, and 38° 01' 49" – 38° 13' 16" East. The average terrain gradient is 30%, and altitudes range from 1.100 m to 1.500 m above sea level. Dominant tree species used for production purposes are natural oriental spruce (*Picea orientalis* Link.) and oriental beech (*Fagus orientalis* Lipsky). Felling and delimbing operations were carried out via chainsaws. Agricultural and skidder (MB Trac 900) are mostly represented as off-road machines and have been widely used (Çalışkan et al., 2017.

Field Data Collection

Timber extraction was done by skidder with cable drawing and on-road skidding system. Measured data for the timber operations have been recorded in study forms. Time values for each stage have been measured as 1/100 minute (PM) using a chronometer, the amount of work done has been determined in units and as m^3, factors that have an impact on the work done (tree type, diameter, height, ground slope, cable drawing distance, number of logs, log volume, skidding distance) have also been recorded in the work form. No intervention was made on the workers regarding issues such as starting and stopping of work, breaks, pauses, dealing with other operations.

Variables that were considered to have an impact on the work time for skidder timber extraction operations have been evaluated as $X_{ii}\left(X_{11}-X_{17}\right)$ and expressed in numerical values. These variables have been briefly explained in *Table 1*.

Continuous time measurement method was used for time measurements and the work phases, total turn time and waiting times were determined using a digital chronometer. The measured time values were for a two person working group with units of 1/100 minute. Work phases and related time values have been expressed as $y_{ii}\left(y_{11}-y_{21}\right)$ for tractor timber extraction operations and related time values have been briefly explained in *Table 1*.

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Measurements and observations have been carried out related with the timber extraction operations for spruce trees using skidder (preparation time on skidder, pulling time to empty cable, hooking time, time to take the load, wait time to obstacle, waiting time to cable dissolution, waiting time, skidding time, unhooking time, stacking time).

Table 1. *Work phases and their descriptive statistics*

Work phases	*Aver.*	*Std. Dev.*	*min.*	*max.*	Work phases	*Aver.*	*Std. Dev.*	*min.*	*max.*
y_{11} : Preparation time on Tractor	72.00	49.74	0.00	205.0	y_{fa} : Total activity(skidding) time	936.0	462.3	250.0	2800
y_{12} : Pulling time to empty cable	143.0	88.28	10.00	420.0	y_{tr} : The tractor is actively operating time	327.0	157.1	60.00	730
y_{13} : Hooking time	160.0	201.8	10.00	980.0	y_{ge} : For cable drawing, actual skidding time	609.0	357.9	130.0	2080
y_{14} : Time to take the load	146.0	88.55	20.00	470.0	X_{11} : Cable haulage distance	26.92	15.45	2.00	90.00
y_{15} : Wait time to obstacle	60.00	12.88	0.00	550.0	X_{12} : Land slope	57.08	12.48	25.00	85.00
y_{16} : Waiting time to cable dissolution	9.00	36.65	0.00	210.0	X_{13} : Diameter of logs	51.48	19.70	17.00	100.00
y_{17} : Load take-off time	34.00	64.83	0.00	300.0	X_{14} : Length of logs	6.61	3.90	1.00	24.00
y_{18} : Waiting time	192.0	731.8	0.00	6340	X_{15} : Number of log	3.15	3.09	1.00	15.00
y_{19} : Skidding time	40.00	46.90	0.00	210.0	X_{16} : Log volume	0.96	0.72	0.09	3.74
y_{20} : Unhooking time	92.00	50.35	0.00	230.0	X_{17} : Skidding distance on the road	9.67	11.13	0.00	50.00
y_{21} : Stacking time	36.00	68.21	0.00	250.0					

In addition, times for work groups have been determined as such by combining certain work phases:
Active operating time for the tractor(skidder):

$$y_{tr} = y_{11} + y_{14} + y_{17} + y_{19} + y_{21} \quad \text{(Eq.1)}$$

Real skidding time required for cable drawing:

$$y_{ge} = y_{12} + y_{13} + y_{14} + y_{15} + y_{16} + y_{20} \quad \text{(Eq.2)}$$

Total activity time:

$$y_{fa} = y_{tr} + y_{ge} \quad \text{(Eq.3)}$$

The definitions of all the y parameters mentioned in the equations are shown in *Table 1*. The ANN models were generated using Matlab software. Statistical analyses were carried out via “SPSS 21.0” software.

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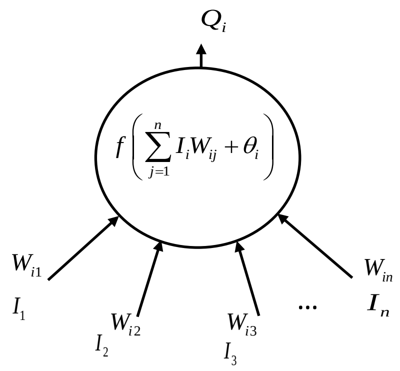
Artificial Neural Network (ANN) modelling approach

General background

ANN is a methodology developed based on the biological operating principle of the human brain which is applied on complex problems. An artificial neural network has three main elements: neurons, connections, and training rules (*Figure 1*) (Dağlı, 1994; Fausett, 1994; Haykin, 1994). In addition, an ANN is comprised of three layers with interconnected neurons which are input layer, output layer and hidden layer. The hidden layer just receive signals from the input layer and send signals to the output layer and their number is determined by way of trials (Benli, 2002).



Here;
I_j *: input signal from the jth neuron*
W_{ij} *: connection weight for the connection from the jth neuron to the ith neuron*
θ_i *: initial value of the ith neuron*
O_i *: output signal of the ith neuron*
f (..) : activation function

Figure 1. *Topology of a Neuron*

One of the most important aspects of an ANN is the connections that enable the neurons to transfer data to each other with weight values (w_{ji}). The weight values have an impact on each input of every operating element (Yıldız, 2001). Training of an ANN is defined as making changes in the weights matrix. It can be classified in two groups as supervised and unsupervised learning (Dağlı, 1994; Karaman and Çalışkan, 2009): MLP and CFBP methods have been used in this study for the prediction of the total time during log skidding operations.

Multiple Layer Perceptron (MLP)

Back propagation (BP) algorithm is used for training MLP networks in this study since it is easy to understand and prove mathematically. The BP artificial neural network models have already been described and are used widely (Rumelhart et al., 1986; Fausett, 1994; Haykin, 1994; Özçelik et al., 2010).

BP algorithm uses two parameters that control the speed at which training takes place. The learning coefficient determines the amount of change in the weights. It is observed that generally values between 0.2 and 0.4 are used and that the value of 0.6 yields the most successful results (Öztemel, 2003). The momentum coefficient plays a role on training performance. It is observed that selecting a value ranging between 0.6 and 0.8 would be best (Öztemel, 2003). Levenberg-Marquardt is highly recommended for neural networks since it is one of the most efficient algorithms (Yu et al., 2011). Levenberg–Marquardt (LM) algorithm has been developed by Kenneth Levenberg and Donald Marquardt (Yu et al., 2011). Considering the features of the problem in this

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study, LM (trainlm) was chosen as the training function. Network architecture, training rate and momentum factor have been determined in our study after examining different combinations. The general structure of MLP is shown in *Figure 2*.

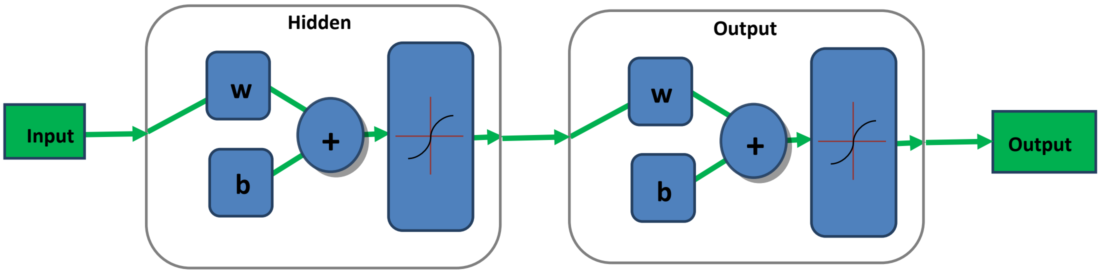

Figure 2. *Multilayer Perceptron (MLP) network architecture*

Cascade Forward Back Propagation (CFBP)

Different than MLP, the input values in CFBP are connected with all layers. CFBP has a learning property just like MLP (*Figure 3*) (Demuth et al., 2009). Considering the features of the problem in this study, LM (trainlm) was chosen as the training function. Network architecture, learning rate and momentum factor were determined in the study after examining different combinations. The general structure of CFBP is shown in *Figure 3*.

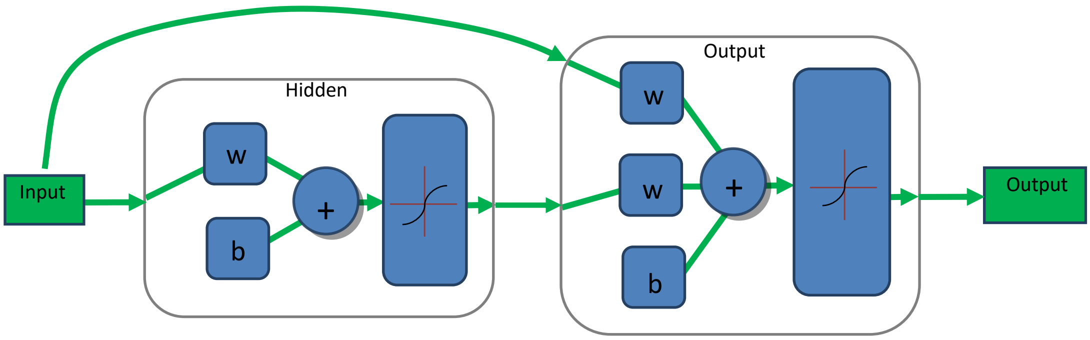

Figure 3. *Cascade Forward Back Propagation (CFBP) network architecture*

Multiple Regression Analysis (MRA)

Regression is one of the methods used for testing whether there is a relationship between two or more variables and to express the relationship between the variables by way of linear or curvilinear equations (Öztürkcan, 2009). Regression analysis using more than one independent variable is called multiple regression analysis.

The general structure of the equation in cases when there is more than one independent variable (such as $x_1, x_2, x_3, ...$);

$$Y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... + \beta_n x_n \pm \varepsilon \qquad \text{(Eq.4)}$$

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where Y: Dependent variable, X_i: Independent variable ($i=1,2,3\ldots n$) β_i: Regression parameters ($i=1,2,3\ldots n$), ε: Random error and n: number of unknown parameters.

Statistical calculations on variables that are independent from (x_{ii}) and dependent on (y_{ii}) measurement results have been carried out as;

- Calculation of the average and deviations.
- Examination of the variables that are effective on the actual time spent for each work phase or the unit time value.
- Examination of the relations between variables.
- And determination of the impact of independent variables on the total time spent for work phases (multiple regression analysis).

Model evaluation criteria

In this study, the corrected determination coefficient (R), Mean Squared Error (MSE), Root Mean Square Error (RMSE) and mean absolute error (MAE) were used as criteria for comparing artificial neural networks (MLP, CFBP) and multiple regression analysis (MRA). Accordingly, high R and low MSE, RMSE and MAE values indicate the best model. MAE and MSE values were close to 0 and the R value was close to 1, thereby indicating that the predicted value strongly converges to the right (Hocking, 1986; Law, 1999; Cho, 2003; Arıkan Kargı, 2014).

a) The Correlation coefficient (R)

$$R=\frac{\sum\left(X_i-\bar{X}\right)\left(Y_i-\bar{Y}\right)}{\sqrt{\sum\left(X_i-\bar{X}\right)^2\left(Y_i-\bar{Y}\right)^2}} \qquad \text{(Eq.5)}$$

b) Mean Squared Error (MSE)

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2 \qquad \text{(Eq.6)}$$

c) Root Mean Square Error (RMSE)

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left(x_i-y_i\right)^2}{n}} \qquad \text{(Eq.7)}$$

d) Mean absolute error (MAE)

$$MAE=\frac{\sum_{i=1}^{n}\left(x_i-y_i\right)}{n} \qquad \text{(Eq.8)}$$

where X_i and Y_i are the observed and predicted data, respectively; $\bar{X}$ and $\bar{Y}$ are the mean of the observed and predicted and n the number of observations in the dataset.

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Results and Discussion

The arithmetic average, standard deviation, max and min values for the actual time values measured with a unit of 1/100 minutes as the variables of observed values regarding the work phases of cable drawing by forest tractor have been calculated and presented in *Table 1*.

Single input variance analysis was used to examine whether the impact of the correlation matrix indicating the relationship between the variables and X_{ii} groups on the values of y_{ii} was statistically significant or not.

The developed ANN models (both MLP and CFBP models) used Cable haulage distance (X_{11}), Land slope (X_{12}), Diameter of logs (X_{13}), Length of logs (X_{14}), Number of logs (X_{15}), Log volume (X_{16}) and Skidding distance on the road (X_{17}), as input variables and the Total activity time (Skidder, y_{fa}) as the output variable.

In this study, all data were first normalized (0-1) and training, validation and testing data sets that are randomly partitioned into training (65% of all data). The validation (10%) and test data sets (the remaining 25%) were used for conquering general patterns between input and output variable while building the ANN model. The training set adjusts the connection weights and the parameters of the model; the validation set checks the performance of the model through the training process and stops the training to avoid overfitting; while the testing set evaluates the trained ANN performance and generalization power (Ghajar et al., 2012a,b; Ghorbani et al., 2016).

A typical MLP model with a BP algorithm is constructed for predicting the total activity time for skidder. The most important characteristic of multi-layered artificial neural networks is that they can be designed to contain more than one hidden layer. However, it has been determined that networks designed with one or two hidden layers display a good performance, whereas networks with more than one or two hidden layers do not have any advantage (Yeşilnaçar et al., 2005; Rumelhart, 1986). The number of neurons in the hidden layer is also an effective element in network performance. In some cases, networks with two hidden layers with a smaller number of neurons may have a better performance in comparison with networks that contain many neurons in one hidden layer (Yılmaz, 2009).

In this study, the number of neurons in the hidden layer was determined by trial and error. In this context, one hidden layer with 30 neurons was included in the model. Neurons ranging between 1 to 40 were given to each layer for determining the number of neurons included in the hidden layer. Each model was tested 15 times to determine the best model for our study. Therefore, the most suitable model was identified as the model with a 7-30-1 network structure. This study, the hyperbolic tansig transfer function was used between the input and hidden layers, and a pureline transfer function was used between the hidden and output layers. The Levenberg-Marquardt (LM) method was used for the optimization of the algorithms.

In this model, each combination of learning rates and momentum factors were tested for different numbers of hidden neurons. The network was trained in 930 epochs using the LM learning algorithm with a learning rate of 0.001 and a momentum coefficient of 0.3. This was the best combination that conducts to the smaller values of R, MSE, RMSE and MAE in *Table 2*. Regression values for the data used in the training, validation and testing of the MLP have been given in *Figure 4*.

Figure 4 shows the R values graph for the training, test and validation stages of the studied model. The values determined were R= 0.9027 for the learning stage, R= 0.7767

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for the test stage, R= 0.7427 for the validity testing of the model and R=0.8536 in total. *Figures 5 and 6* show the graphs comparing the model predictions and observed values for the MLP model. It can be observed from *Figures 5-6* that the values of the total time during log skidding operations were usually predicted near the observed value.

Table 2. *Regression Equalities for calculating the total activity time of timber extraction via skidder*

Nu	Total Time	*b*	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	R-sq
1	y_{fa}	55.39	15.09	2.34	-3.05	6.73	26.14	385.4	-1.16	.777
2	y_{fa}	71.14	14.95	2.05	-3.07	6.21	26.70	380.3		.776
3	y_{fa}	137.0	14.88	1.97	-3.82		26.07	404.0		.775
4	y_{fa}	261.9	14.80		-3.90		25.59	399.8		.773

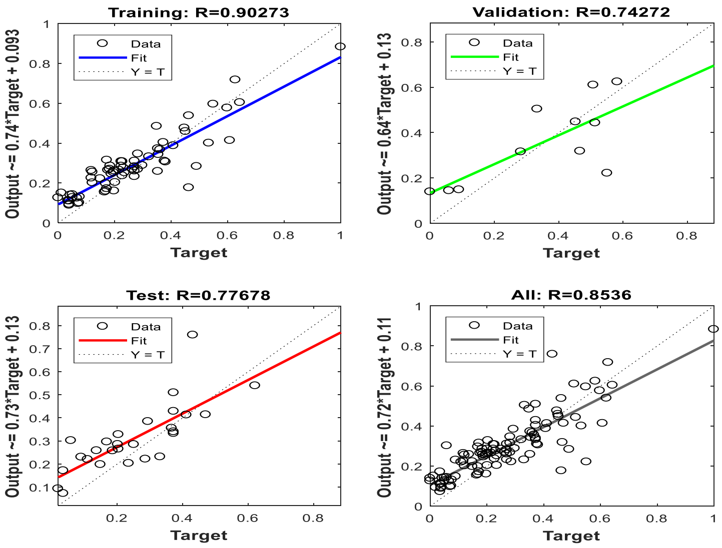

Figure 4. *Training, test, validation distribution graphs for the MLP prediction model*

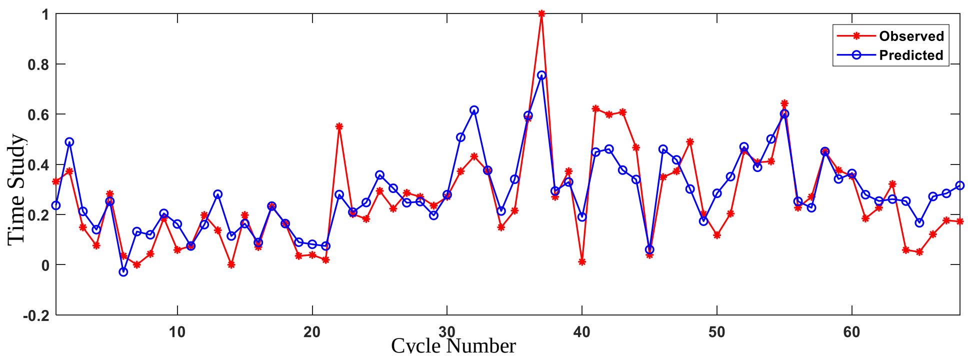

Figure 5. *Comparison of predicted(blue line) and observed(red line) values for training sets using MLP*

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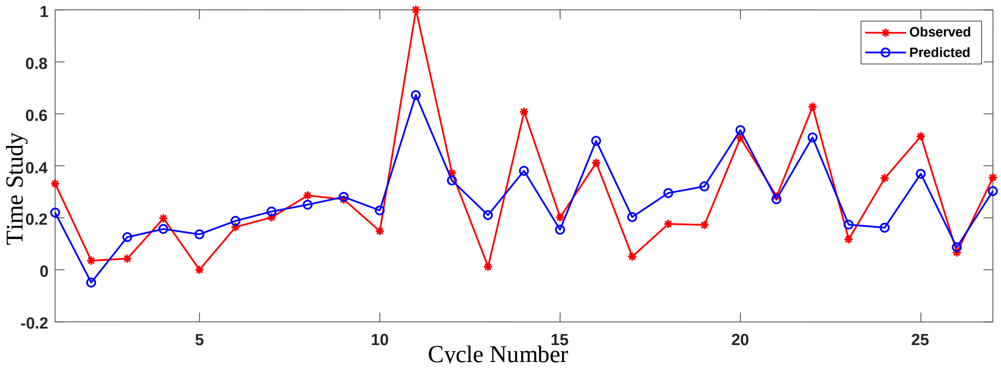

Figure 6. *Comparison of predicted (blue line) and observed (red line) values for test sets using MLP*

The hyperbolic tansig transfer function was used between the input and hidden layers, and a pureline transfer function was used between the hidden and output layers in CFBP model which gave the best results. The LM method was used for the optimization of the algorithms. CFBP model had a single hidden layer with 16 neurons. According to results, the most suitable model for CFBP is 7-16-1 network structure. In this model, the network was trained in 900 epochs using the LM learning algorithm with a learning rate of 0.001 and a momentum coefficient of 0.3. This was the best combination that conducts to the smaller values of R, MSE, RMSE and MAE in *Table 2*. Regression values for the data used for the training, validity and testing of the CFBP model have been given in *Figure 7*.

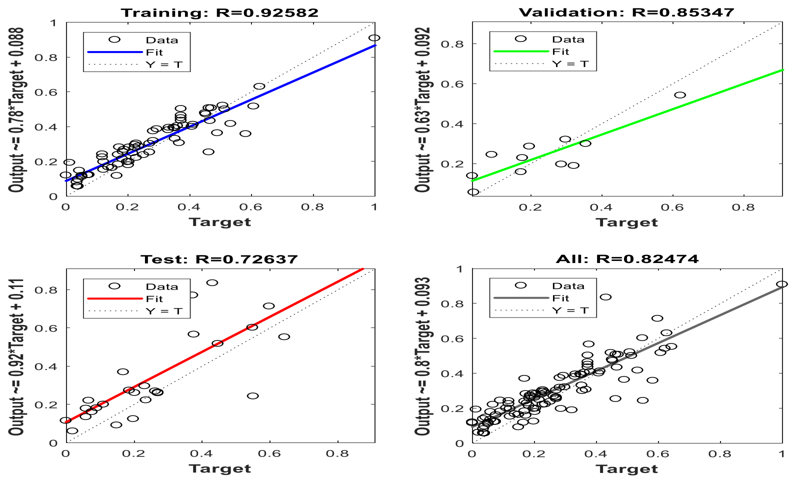

Figure 7. *Training, test, validation distribution graphs for the CFBP prediction model*

Figure 7 shows the R value graphs for the training, test and validation t stages for the studied model. The values determined were R= 0.9258 for the learning stage, R= 0.7263 for the test stage, R= 0.8534 for the validity testing of the model and R= 0.8247 in total. *Figures 8 and 9* show the graphs comparing the model predictions and observed values for the CFBP model.

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It can be observed from *Figure 8-9* that the values of the total time during log skidding operations are usually predicted near the observed value.

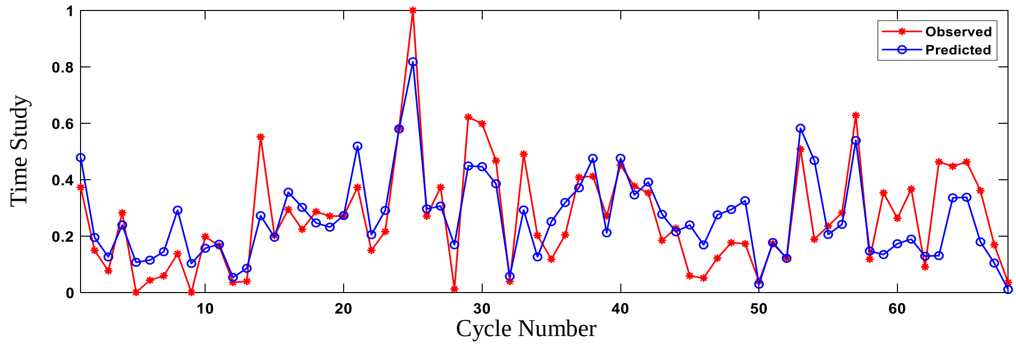

Figure 8. *Comparison of predicted and observed values for training sets using CFBP*

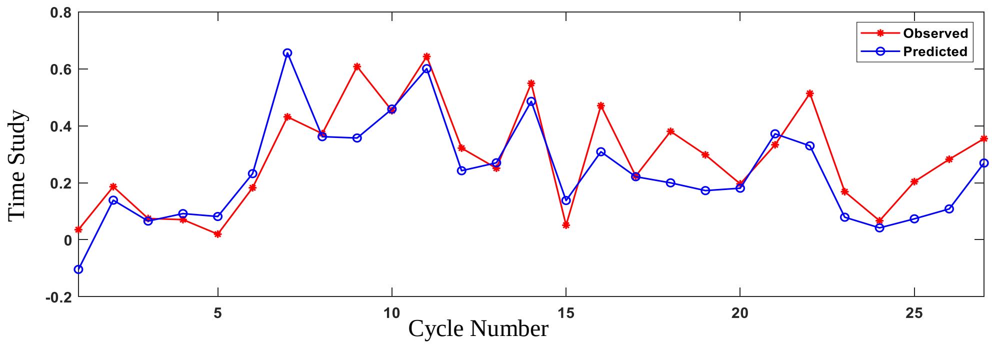

Figure 9. *Comparison of predicted and observed values for test sets using CFBP*

Alternative equalities have been generated via multiple regression analysis. Operations carried out for the timber extraction total activity time with forest tractor (y_{fa}) have been given in detail.

Regression equalities based on the $y_{fa} = f\left(X_{11}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}, X_{17}\right)$ relationship have been given in *Table 3*. Consistency of the equation was tested using the coefficients obtained from the regression equation and test data. Graphs that compare the model predictions obtained from the MRA model and the observed values have been given in *Figure 10*.

Table 3. *A Comparison of the MLP, CFBF and MRA Models*

Model	*Topology*	*R*	*MSE*	*RMSE*	*MAE*
MLP	7-30-1	0.85	0.0098	0.0991	0.0760
CFBP	7-16-1	0.82	0.0125	0.1120	0.0784
MRA	7-1	0.77	0.0127	0.1126	0.0877

It can be observed from *Figure 10* that the values of the total time during log skidding operations usually predicted near the observed value.

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The performances for predicting total activity time for skidder are compared using three techniques of MLP, CFBP and MRA. The values of performance measures are given in *Table 3*.

Values of R, MSE, RMSE and MAE were compared at the end of the study for determining the algorithm with the best performance. MLP had the best performance in the study followed by CFBP and finally MRA with the lowest performance.

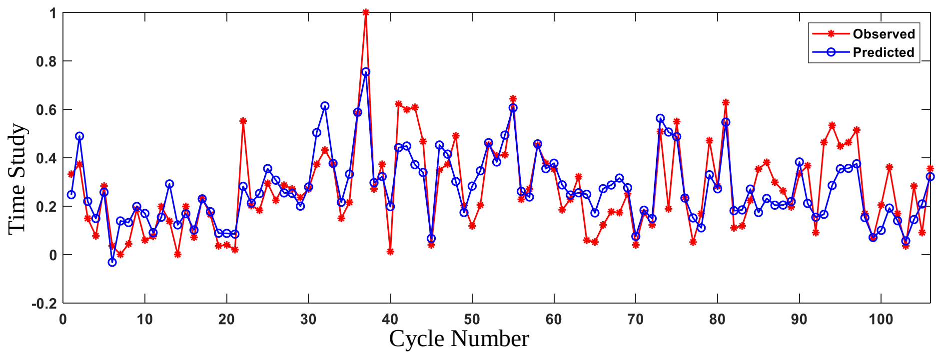

Figure 10. *Comparison of predicted and observed values using MRA*

Conclusion

The aim of this study was to investigate the feasibility of two different reputed types of ANNs including MLP, CFBP and compare them with the MRA model with regard to predicting the total time during log skidding operations stations in Eastern Blacksea region (Giresun Forest District Directorates) of Turkey.

Determination coefficient (R) and the expressions that indicate the error variance (MSE, RMSE and MAE) have been taken into consideration for determining the model with the best results. Accordingly, the model with high R and low MSE, RMSE and MAE values was taken into consideration as the best model. The R values obtained in the study were determined to vary between 0.85 and 0.82 for MLP and CFBP and as 0.77 when multiple regression was used.

Thus, it can be observed that artificial neural networks have higher prediction accuracy in comparison with multiple regression analysis and yield results with lower error values. In this case, it can be predicted that artificial neural networks may be preferred in cases when regression analysis predictions are not met and the analysis cannot be carried out.

MLP yielded better results in comparison with CFBP when ANN methods are compared among themselves for the prediction of total time during log skidding operations stations. The results of this study can be used for preparing and inspecting machine operating programs and for calculating production cost. MLP models can be used reliably for calculating the operating time of different land and operating conditions.

The results of this study can be used for determining the time dependent machinery demand to be used in timber extraction operations by private companies, for cost calculation and for putting forth the alternatives to carry out the work at minimum cost.

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