APPLICATION OF ARTIFICIAL NEURAL NETWORKS AND PARTICLE SWARM OPTIMIZATION FOR TIMBER EXTRACTION WITH CABLE CRANE

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Abstract. The fact that forest areas in Turkey and the world are located at high and steep mountainous areas makes it more difficult to extraction the wood raw material. Therefore, the retreat of forest areas to mountainous areas has brought cable crane to the forefront. Thus, it has become possible to solve complex problems by way of artificial intelligence techniques. The purpose of this study was to determine the impact of factors related with timber extraction via URUSMIII cable crane on total time via Artificial Neural Network (ANN), Particle Swarm Optimization (PSO) and Multiple Regression Analysis (MRA). The data were obtained from oriental spruce timbers which were acquired from spruce stands in the Artvin Forest Directorate, located at NE Turkey. The factors with impact on total time (ground slope, line slope, lateral pull, number of logs, diameter of logs, length of logs, log volume, yarding distance) were measured along with the total time. Determination coefficient (R) and the expressions that indicate error variance (MSE, RMSE and MAE) were taken into consideration for determining the model with the best results. PSO model was determined as the best structure (R = 0.85 MSE = 0.0143, RMSE = 0.1194, MAE = 0.0839): in this study according to the obtained results. The results indicate that PSO had the best performance in the study followed by ANN and finally MRA with the lowest performance. The PSO model can be used for similar conditions on the planning of forest operation, the control of applications and the determination of unit of price for forest workers.
Keywords: *forest operations, timber extraction, total time, artificial neural networks, particle swarm optimization, multiple regression analysis*

Introduction

The need for timber continues to increase in Turkey every day; however forest areas continue to decrease rapidly. The transport stage is quite difficult, expensive and time-consuming in forest management. It is an important issue that the product is extracted with the minimum damage to itself and the environment as well as with minimum loss of quality.

Cable crane systems are used for extraction purposes in many mountainous regions in the world. Since majority of the forests in countries such as Austria, Czech Republic, Japan, Norway and Scotland are located in mountainous areas, cable-crane systems are frequently used for extraction purposes (Russell and Mortimer, 2005; Huber and Stampfer, 2015; Proto and Zimbalatti, 2015)

As is known, forest cable-crane systems are manufactured in whole and are used for carrying heavy forest assets from the air over distances of 300-2000 m. According to yarding distance, these are called as short (< 300 m), middle (300-800 m) and long (800 <) distance skylines (Acar et al., 2005).

URUSMIII cable crane was started to be used in our country during the late 1970s. Although it is not very widespread throughout the country, it is used extensively for timber extraction in the Artvin region (Acar and Şentürk, 2000).

Cable cranes are quite different in comparison with other extraction methods. The volume is limited for manual extraction. Sliding is one-directional and can be carried out in case the incline is high. Animal-powered extraction cannot be performed from the top to the bottom in steep areas. Whereas for tractor extraction there are various disadvantages such as the issue that transportation cannot be made from the top to the bottom as well as short cable length.

Artificial Neural Networks (ANN) are used as a popular method by many different researchers in different engineering applications. ANN is a structure that based on the learning model of the human brain which contains neurons and is comprised of different layers by combining these neurons using different weights (Haykin, 1999). ANN is a very strong method especially for data modelling when regression coefficients are low (Esteban et al., 2009).

Heuristic optimization is used recently in algorithms in addition to artificial neural networks for improving the success and/or speed of artificial neural networks (Bağış and Çetin, 2009; Liu et al., 2008; Özbeyaz, 2010). Particle Swarm Optimization (PSO) which is one of the heuristic methods has been used successfully in many areas due to reasons such as the ease with which it can be implemented, the low number of parameters that need to be adjusted and the fact that it operates with real numbers. One of these is the training of artificial neural networks (Tamer and Karakuzu, 2006; Delice, 2008; Hema et al., 2008; Gu et al., 2009).

Various studies have been carried out on timber extraction operations during which time studies have been carried out for cable crane URUSMIII (Aykut et al., 1997; Çağlar, 2002; Baldini and Pollini, 1998; Heinrich, 1998; Trzesnowski, 1998; Ledoux and Huyler, 2000; Rieger, 2001; Krpan et al., 2001; Acar et al., 2005; Öztürk and Demir, 2007; Zimbalatti et al., 2009; Zimbalatti and Proto, 2010; Çalışkan, 2015).

The use of Artificial Neural Networks (ANN) and Particle Swarm Optimization (PSO) in timber extraction is at a starting stage in Turkey. Hence, there are no studies in literature which compare the performance of ANN and PSO with other models.

The purpose of this study was to examine the impact of factors related with the interaction of timber extraction with URUSMII cable crane on total time via ANN, PSO and MRA. The data were obtained from oriental spruce timbers from spruce stands in Artvin Forest Directorate, in NE Turkey.

Materials and methods

Study area

This study was carried out in the Ardanuç forest planning unit covering an area of approximately 76817.0 ha of forest with the growing stock 5.9 million m³ in the Artvin province in the northeastern Black Sea region of Turkey. The area was located between 41° 12' 34" North, and 41° 48' 55" East. Dominant tree species used for production purposes are natural oriental spruce (*Picea orientalis* Link.), and nordmann fir (*Abies nordmanniana* Stew) and oriental beech (*Fagus orientalis* Lipsky). The climate in Artvin is mild with humid summers. Annual precipitation and temperature averages approximately 700 mm and 13 °C, respectively (Akman, 1990). Felling and delimbing operations were used to be carried out via chainsaws. Cable crane Urus (MIII) is mostly represented as off-road machines and have been widely used (*Fig. 1*). Urus MIII cable crane is generally used in uphill yarding operations, ranging from 500 to 600 m and combining with Mercedes Benz Unimog U1500 truck. Four workers are employed in

operating the cable crane. The set up duration of cable crane is between 10 and 16 h and pull up duration is between 4 and 8 h depends on terrain conditions. The number of safety ropes ranges between 2 and 4. The basic characteristics of the URUSMIII were given in (Çağlar et al., 2007; Öztürk and Şentürk, 2016).

Figure 1. *Urus MIII cable crane*

Field data collection

Timber extraction was carried out using cable crane. Measured data for the timber operations have been recorded in study forms. Time values for each stage have been measured as 1/100 min (PM) using a chronometer, the amount of work done has been determined in units of m^3, factors that affect the work done (ground slope, line slope, lateral pull, number of logs, diameter of logs, length of logs, log volume, yarding distance) have also been recorded in the study 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} (X_{11}-X_{18}) and expressed in numerical values. These variables have been briefly explained in *Table 1*.

Repetition 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 obtained for a two person working group in units of 1/100 min. Work phases and related time values have been expressed as Y_{ii} (Y_{11}-Y_{19}) for cable crane timber extraction operations and related time values have been briefly explained in *Table 1*.

Measurements and observations were carried out for timber extraction operations for spruce trees using cable crane (Hauling back of empty carriage *(Y_{11})*, Descending of bundle hook *(Y_{12})*, Pulling of hook to logs *(Y_{13})*, Pulling of loaded hook to carriage *(Y_{14})*, Moving of loaded carriage to landing site *(Y_{15})*, Descending of loaded hook to ground *(Y_{16})*, Unhooking of loads *(Y_{17})*, Pulling backwards of empty carriage *(Y_{18})*, Nonworking time (which covers spare and delay time of workers *(Y_{19})*, Total activity time *(y_{fa})*.

Total activity time (*Eq. 1*):

$$y_{fa} = y_{11} + y_{12} + y_{13} + y_{14} + y_{15} + y_{16} + y_{17} + y_{18} + y_{19} \qquad \text{(Eq.1)}$$

The ANN-PSO models were generated using Matlab software. Statistical analyses were carried out via "SPSS 21.0" software.

Artificial neural network (ANN)

Artificial neural networks are mathematical models inspired by the structure and behavior of the human brain (Olden et al., 2008). The ANN network includes three main layers: input, hidden and output. These layers are used for data input, data transmission and data output respectively. The hidden layer function is used to transfer the results to the output layer (Fausett, 1994; Haykin, 1994). The output of each neuron can be written as (*Eq. 2*):

$$y_i = f\left(\sum w_{ij} x_i\right) \qquad \text{(Eq.2)}$$

where y_i represents the input that a single node j receives. The function f can be a simple threshold, sigmoid or hyperbolic tangent function. The weights between the nodes i and j are denoted as w_{ij}: x_i represents the output from node i.

Whereas the input layer in this study was comprised of 8 neurons as ground slope, line slope, lateral pull, number of logs, diameter of logs, length of logs, log volume and yarding distance; there was only 1 neuron of Total activity time (y_{fa}) in the output layer. The number of neurons in the hidden layer varies according to the characteristic of the problem.

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

The hyperbolic tangent sigmoid (tansig) transfer function presented by the following equation was used between the input and hidden layers in the model in this study (Fausett, 1994). A linear (pureline) transfer function was used between the hidden and output layers.

NET: Weighted sum (*Eq. 3*)

$$f\left(NET_i\right) = \frac{1}{1 + e^{-NET_i}} \, , \; f\left(NET_i\right) = NET_i \qquad \text{(Eq.3)}$$

BPA uses two parameters that control the speed at which training takes place. The learning coefficient determines the amount of change in the weights. It was observed that values ranging between 0.2 and 0.4 are generally used and that the value of 0.6 yields the most successful results (Öztemel, 2003). The momentum coefficient has an impact on training performance. It was observed that selecting a value ranging between 0.6 and 0.8 would be best (Öztemel, 2003).

Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) was first developed by Kennedy and Eberhart (1995) inspired by the behaviors of bird swarms when trying to find food. The

population is defined as swarm in this algorithm, whereas each individual is defined as particle. These particles are accepted to be flowing in multi-dimensional space. PSO can be applied successfully in many areas such as artificial neural network training (Zhao et al., 2005; Awad, 2006).

PSO is started with a group of random values (particle swarm) and the optimum solution is tried to be determined by way of iterations. Particle positions are updated according to the best two values in each iteration. The first value includes the coordinates that provides the best solution for that particle until that point. This value is defined as "pbest" and should be stored in memory. Whereas the other best value includes the coordinates that provides the best solution for all particles in that population until that moment. This is the global best value and is denoted as "gbest". For example, let us assume that there are n particles comprised of D parameters.

Every particle has its own position, velocity and best solution. The PSO method can be presented as follows (Elbeltagi et al., 2005; Al_Janabi et al., 2018):

The swarm position in a D space of the *i*th particle can be presented by (*Eq. 4*):

$$X_I = \left(X_{i1}, X_{i2}, X_{i3}, ..., X_{iD} \right), \quad i = 1, 2, 3, .., N \tag{Eq.4}$$

Whereas velocity of each particle can be represented as (*Eq. 5*):

$$V_I = \left(V_{i1}, V_{i2}, V_{i3}, ..., V_{iD} \right), \quad i = 1, 2, 3, .., N \tag{Eq.5}$$

Each particle maintains a memory of its previous best position. The best swarm position is given by (*Eq. 6*):

$$pbest_I = \left(pbest_{i1}, pbest_{i2}, pbest_{i3}, ..., pbest_{id} \right), \quad i = 1, 2, 3, .., N \tag{Eq.6}$$

gbest is unique for all particles in each iteration (*Eq. 7*):

$$gbest_I = \left(gbest_{i1}, gbest_{i2}, gbest_{i3}, ..., gbest_{id} \right), \quad i = 1, 2, 3, .., N \tag{Eq.7}$$

A particle velocity should be updated and the following equation can be used (*Eqs. 8-9*):

$$V_i^{k+1} = V_i^k + c_1 r_1^k \cdot \left(pbest_i^k - x_i^k \right) + c_2 rand_2 \cdot \left(gbest_i^k - x_i^k \right) \tag{Eq.8}$$

$$Fitness = \sum_i \left(Y_i - X_i V \right)^2 \tag{Eq.9}$$

where the parameters of c_1, c_2 are constants and r_1, r_2 are random numbers ranging between 0–1. $pbest_i$ is the best local solution of the *i*th particle for the iteration number up to the *i*th iteration. The best global solution of all particles is g_{best}. The "inertia weight" w controls the effect of the previous velocity of the particle on the current one. If the value of w is greater than 1, it means that the particle favored searching over exploitation; whereas a w value of less than 1 is an indication that the particle gave more importance to the current best positions (Al_Janabi et al., 2018).

Network architecture, training rate and momentum factor have been determined in our study after examining different combinations. Several different ANN models were developed and tested in order to determine the optimal number of neurons in the hidden layer by trial and error estimates. A single hidden layer was used to significantly reduce the computational time. The general structure of ANN is shown in *Figure 2*.
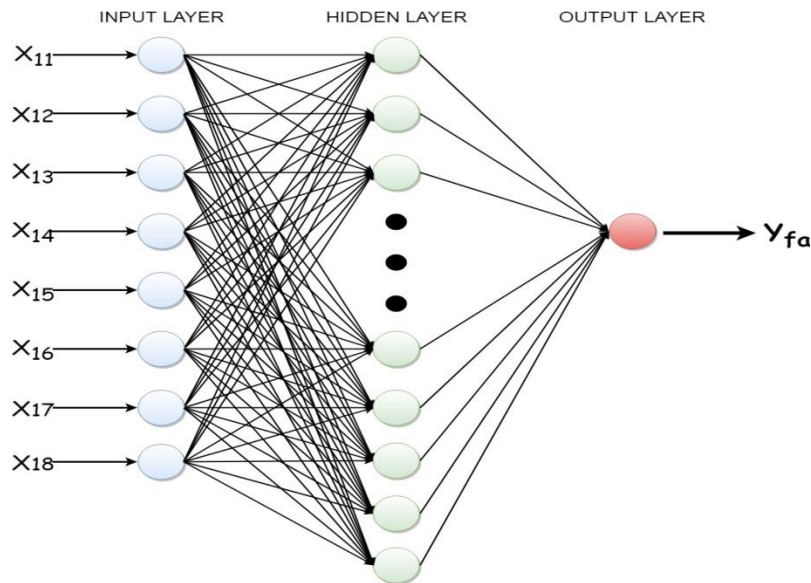

Figure 2. *Schematic diagram of ANN model*

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 $\left(\text{such as } X_1, X_2, X_3,...\right)$ (*Eq. 10*):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... + \beta_n x_n \pm \varepsilon \qquad \text{(Eq.10)}$$

where Y: dependent variable, *Xi*: independent variable $\left(i=1,2,3,..,N\right)$ β_i: regression parameters $\left(i=1,2,3,..,N\right)$, ε: random error and *n*: number of unknown parameters.

In this study, ground slope, line slope, lateral pull, number of logs, diameter of logs, length of logs, log volume, yarding distance are selected as the independent variables and total time is selected as the dependent variable.

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

Model evaluation criteria

In this study, the performance of different predictive models is evaluated by using statistical measures including 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 ANN, PSO and 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, 1976; Law, 1999; Cho, 2003; Arıkan, 2014).

a) The correlation coefficient (R) (*Eq. 11*):

$$R = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 (Y_i - \bar{Y})^2}} \tag{Eq.11}$$

b) Mean squared error (MSE) (*Eq. 12*):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{Eq.12}$$

c) Root mean square error (RMSE) (*Eq. 13*):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}} \tag{Eq.13}$$

d) Mean absolute error (MAE) (*Eq. 14*):

$$MAE = \frac{\sum_{i=1}^{n} (x_i - y_i)}{n} \tag{Eq.14}$$

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.

Results and discussion

The arithmetic average, standard deviation, max and min values for the actual time values measured in units of 1/100 min as the variables of observed values regarding the work phases via cable crane 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.

Table 1. *Work phases and their descriptive statistics*

Work phases	Average	Std. dev.	Min.	Max.	Work phases	Average	Std. dev.	Min.	Max.
y_{11}: Hauling back of empty carriage	33.00	17.76	15.00	111.0	y_{fa}: Total activity time	619.0	253.1	275.0	1422
y_{12}: Descending of bundle hook	32.0	21.04	10.00	114.0	x_{11}: Ground slope	70.33	1.69	68.00	73.00
y_{13}: Pulling of hook to logs	167.0	107.2	31.00	500.0	x_{12}: Line slope	51.97	0.23	51.00	52.00
y_{14}: Pulling of loaded hook to carriage	69.22	71.15	60.00	499.0	x_{13}: Lateral pull distance	20.76	0.64	10.00	35.00
y_{15}: Moving of loaded carriage to landing site	233.0	97.55	101.0	447.0	x_{14}: Yarding distance	140.92	61.72	70.00	250.00
y_{16}: Descending of loaded hook to ground	10.00	3.52	4.00	230.0	x_{15}: Diameter of logs	33.76	8.78	22.00	61.00
y_{17}: Unhooking of loads	29.65	23.79	5.00	218.0	x_{16}: Length of logs	5.24	1.05	3.00	8.00
y_{18}: Pulling backwards of empty carriage	7.44	1.43	4.00	12.00	x_{17}: Number of logs	3.15	0.98	1.00	6.00
y_{19}: Nonworking time	36.00	43.90	8.00	314.4	x_{18}: Log volume	1.49	0.69	0.57	3.65

The data were first normalized (0-1) in this study and 70% and 30% of the complete data was used for training and testing respectively. Therefore, 27 testing and 64 training data sets were randomly selected from all land data. The training set adjusts the connection weights and the parameters of the model and the testing set evaluates the trained ANN performance and generalization power (Ghajar et al., 2012a, b).

A network with eight inputs, one hidden layer, and one output was selected in this study. The inputs were: ground slope (x_{11}), line slope (x_{12}), lateral pull distance (x_{13}), extraction distance (x_{14}), diameter of logs (x_{15}), length of logs (x_{16}), number of logs(x_{17}), and log volume (x_{18}); while the output was Total activity time (Cable crane, yfa).

An 8 layer artificial neural network was established in this study and a back-propagation algorithm (BPA) was used as a learning algorithm. The hidden layer and the number of neurons in this layer were determined through trial and error. In this regard, one hidden layer with fifteen (15) neurons was included in the model. Neurons with numbers ranging from 1 to 30 were given to this layer in order to determine the number of neurons that would be included in the hidden layer and each model was tested 10 times to determine the best model for our study. The sigmoid transfer functions were used in input, hidden and output layers in the model. The most suitable model was identified as the model with a network structure of 8-15-1.

Each combination of learning rates and momentum factors were tested for different numbers of hidden neurons. The network was trained in variable epochs via ANN learning algorithm with a learning rate of 0.001 and a momentum coefficient of 0.2. 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 and testing of the ANN have been given in *Figure 3*.
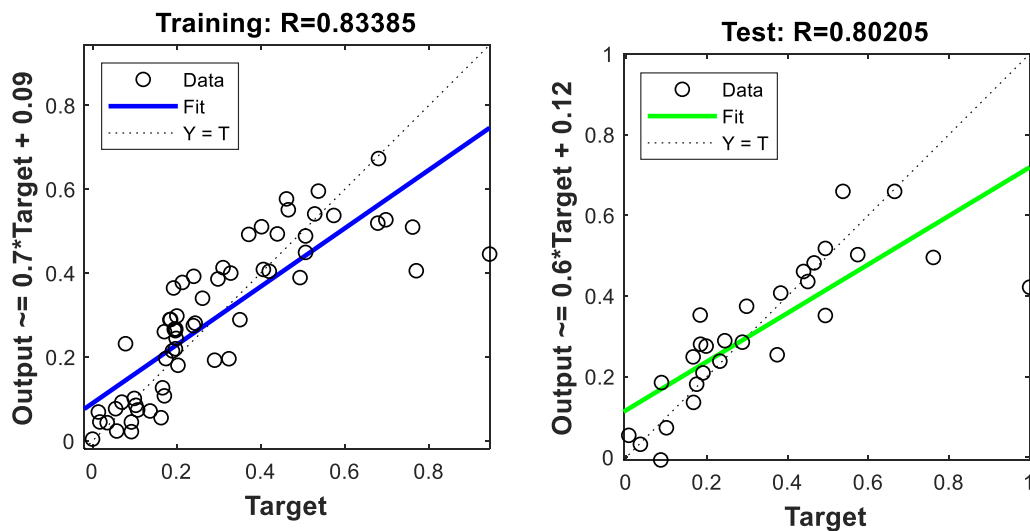
Figure 3. *Training and test, distribution graphs for the ANN prediction model*

Figure 3 shows the R values graph for the training and test stages of the studied model. The values determined were R = 0.8338 for the learning stage and R = 0.8020 for the test stage of the model. *Figures 4* and *5* respectively show the graphs comparing the model predictions and observed values for the ANN model.

It can be observed from *Figures 4* and *5* that the values of the total time during cable crane operations were generally predicted to be close to the observed value.

As mentioned, PSO was used as the artificial neural network algorithm in this study and MSE was applied as a fitness function. The objective of this algorithm is decreasing MSE. The number of data used for training and testing were 64 and 27, respectively.

ANN learning process was started by randomly generating the weights that hold the numerical value of the connections between the layers. These weights express the particle values for PSO. Whereas the number of connections between the layers represents the particle size. The network was setup for each particle and training samples were sent to the network in order. Total error (MSE) was calculated after all values were presented to the network and the obtained value was accepted as the fitness value. This fitness value is determined as the pbest value in the first step; whereas the best fitness value among the particles is determined as gbest. If the fitness value that is the error is not at an acceptable value, the particles are updated with pbest and gbest values. The network was re-established according to the new particle values, the values were resent to the network and fitness value calculation was carried out. These operations are carried out until the best fitness value (gbest) reaches the desired value (very close to 0) or until the maximum number of iterations.

Test process is started if the error is at an acceptable level. This time the network is setup according to the (gbest) particle values, test samples are sent to the input layer in order and the acquired values are provided as the sample output. The last acquired gbest value gives the classification performance of the network when no threshold is applied on the network output.

As a result of the experiments; the optimal parameters for ANN-PSO were determined as; number of hidden neurons = 18, number of particles = 25, number of iterations = 500, (c_1 and c_2 = 2). Particle numbers generally range from 20 to 40 (Tamer

and Karakuzu, 2006). It was stated in the experiments conducted by the researchers on this algorithm that c1 = c2 = 2 gave good results (Shi and Eberhart, 1998; Liping et al., 2005).
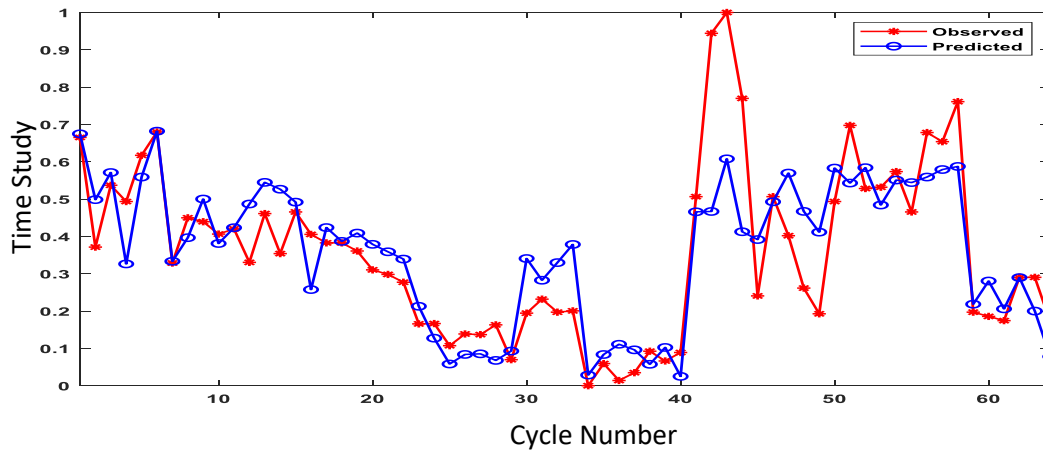

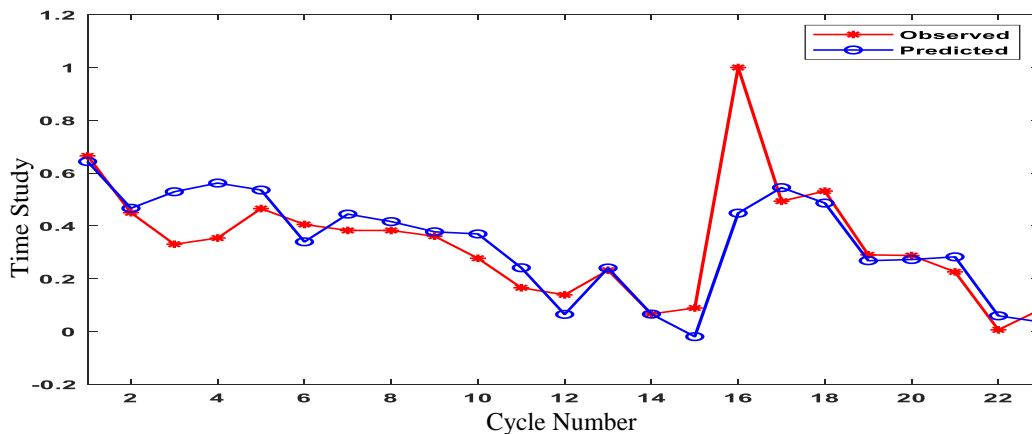**Figure 4.** *Comparison of predicted and observed values for training sets using ANN*

Figure 5. *Comparison of predicted and observed values for test sets using ANN*

This was the best combination that conducts to the smaller values of R, MSE, RMSE and MAE in *Table 2*. *Figures 6* and *7* show the graphs in comparison with the model predictions and observed values for the PSO model.

It can be observed from *Figures 6* and *7* that the values of the total time cable crane operations are generally predicted close to the observed value.

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

Regression equalities based on the $y_{fa} = f(X_{11}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}, X_{17}), X_{18})$ relationship have been given in *Table 2*. 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 8*.

It can be observed from *Figure 8* that the values of the total time during cable crane operations are generally predicted close to the observed value.

Table 2. *Regression equalities for calculating the total activity time of timber extraction via cable crane*

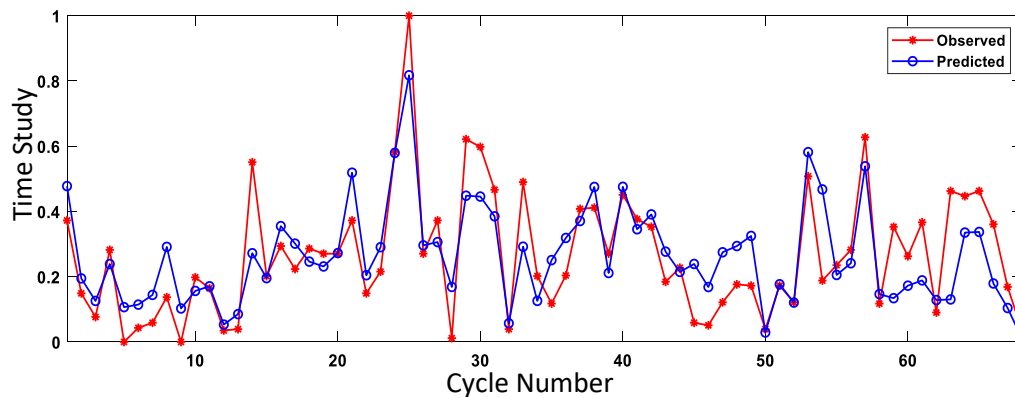| Nu	Total time	b	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	R-sq
1	y_{fa}	-6.14	0.19	0.39	0.13	0.02	-0.01	0.14	-1.5	-0.21	0.699
2	y_{fa}	-6.23	0.19	0.39	0.13	0.02		-0.14	0.16	-0.22	0.698
3	y_{fa}	13.80	0.18		0.13	0.22		0.14	0.49	-0.21	0.697
4	y_{fa}	11.62	0.16		0.14	0.22		0.19	0.27		0.695
5	y_{fa}	10.66	0.15		0.14	0.22			0.17		0.690
6	y_{fa}	10.63	0.14		0.13	0.22					0.685
7	y_{fa}	-0.11			0.13	0.24					0.677

Figure 6. *Comparison of predicted and observed values for training sets using PSO*
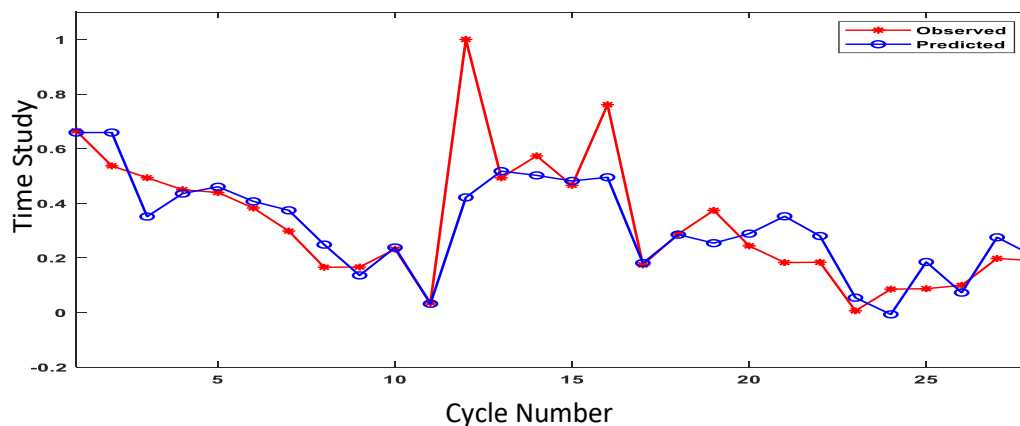

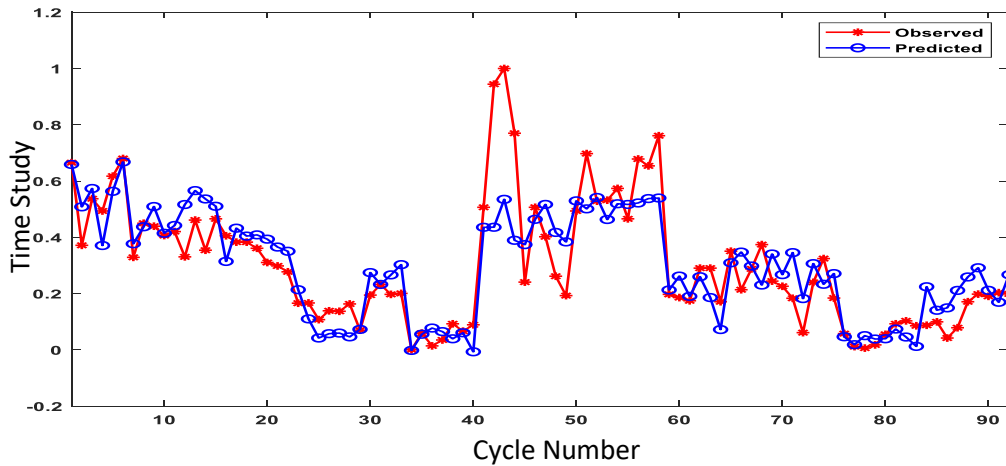***Figure 7.*** *Comparison of predicted and observed values for test sets using PSO*

Figure 8. *Comparison of predicted and observed values using MRA*

The performances for predicting total activity time for cable crane are compared using three techniques as ANN, PSO and MRA. The values of performance measures are given in *Table 3*.

Table 3. *A comparison of the ANN, PSO and MRA, models*

Model	R	MSE	RMSE	MAE
PSO	0.85	0.0143	0.1194	0.0839
ANN	0.83	0.0152	0.1232	0.0907
MRA	0.69	0.0194	0.1434	0.1186

Values of R, MSE, RMSE and MAE were compared at the end of the study for determining the algorithm with the best performance. Based on the results obtained from this study, the PSO has been found to be better than the ANN and MRA models, because the PSO has a higher ability in global search than in ANN and MRA models.

ANN and PSO have been applied successfully in the field of forest modeling. Specifically, artificial neural network approach has been carried out for many objectives such as modeling individual tree survival probabilities (Guan and Gertner, 1995), diameter growth based climatic variables (Zhang et al., 2000); wildlife planning issues (Bettinger et al.,2002), forecasting wood demand (Güngör et al., 2004*)* tree volume (Diamantopoulou, 2005a; Diamantopoulou and Milios, 2010; Özçelik et al., 2008, 2010), tree stem diameters (Diamantopoulou, 2005b, 2006; Leite et al., 2011), predicting forest fire burn areas (Cortez and Morais, 2007), forest planning (Pukkala, 2009), tree felling times (Karaman and Çalışkan, 2009), tree heights (Özçelik et al., 2013), prediction of skidding time (Naghdi and Ghajar, 2012), trunk volume estimates ((Bayati and Najafi; 2013), predicted forest fire burn areas (Safi and Bouroumi, 2013), forest feature extraction (Li et al., 2014), prediction of winching time (Bayati and Najafi; 2015), tree diameter increments (Ercanlı et al., 2016) and describing diameter distribution (Bolat et al., 2016), predicting forest fire (Al_Janabi et al., 2018).

Conclusion

In this study, the impact of factors interacting during timber extraction via URUSMIII cable crane on total time was determined by using ANN, PSO and MRA. The data were obtained from oriental spruce timbers from spruce stands in Artvin Forest Directorate located at NE Turkey. In the study, 70% and 30% of the complete dataset were used for training and testing, respectively. Therefore, 27 testing and 64 training data sets were randomly selected from all land data.

Determination coefficient (R) and the expressions that indicate error variance (MSE, RMSE and MAE) were taken into consideration for determining the model with the best results. The R values obtained in the study were determined to vary between 0.85 and 0.83 for PSO and ANN respectively and as 0.69 when MRA was used.

Based on the results obtained from this study, it was determined that the performance of PSO model was better compared to ANN and MRA. The study also indicates that PSO may be used efficiently in forestry operations.

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