Journal of Agricultural Science; Vol. 14, No. 3; 2022
ISSN 1916-9752 E-ISSN 1916-9760
Published by Canadian Center of Science and Education

Prediction of Mechanical Availability in Mechanized *Eucalyptus* Forest Harvesting Using Artificial Neural Networks

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Received: November 11, 2021 Accepted: January 12, 2022 Online Published: February 15, 2022

doi:10.5539/jas.v14n3p157 URL: https://doi.org/10.5539/jas.v14n3p157

Abstract

The planted forests in Brazil and in the world represent a significant slice of the forest sector in general, having the mechanization of activities, especially forest harvesting, is of great importance in the process. The objective was to estimate, through the use of Artificial Neural Networks, more reliable configurations to estimate the mechanical availability of harvester forest harvester-type equipment. The analyzed data were compiled and organized in a database of production monitoring of a company in the forest sector located in the southeast region of Brazil, later trained and validated according to neural network techniques. A trend was observed for the Resilient Propagation algorithm, where among all the trained ANNs, those that obtained the best R2 correlation values, the Quickpropagation training algorithm presented a correlation coefficient between the estimated values and observed values considered high, 0.9908, demonstrating that the trained networks are reliable. The Backpropagation training algorithm had a lower result, with only 75.77% of the estimated mechanical availability variation being explained by the observed mechanical availability. However, the application of artificial neural networks offers a practical solution to the problem of estimating mechanical availability quickly and accurately.

Keywords: artificial intelligence, forestry, harvest planning

1. Introduction

With the highlight for the cultivation of plantes forest of Eucalyptus and Pinus, Brazil produces several products from these forests, such as pulp and paper, industrialized wood panels, charcoal, lumber, firewood, among others, supplying the domestic and international market. A production chain of highly demanded needs a constant search for new technologies, continuous improvement and optimization of processes, become increasingly explored (Brazilian Tree Industry, 2020).

The mechanization of the forest harvesting activity is going through moments of great innovation and technological advances, since it come to represent up to 50% of the costs of the final product when added to forest transport. Globally, this is an issue that can affect the profitability of companies and promote systemic losses to the process, however the sector still suffers from a lack of reliable data for the choice either of the system and/or the most suitable and and economically feasible equipment for the process (Nascimento et al., 2011).

Simões et al. (2010) reported that according to the last years occurred an intensification of the forest harvesting mechanization, leading to a continuous process of operational and economic yields evalution, highlighting to the great percentage of production costs aggregated to commercial plantations.

A good mechanical maintenance provides to the forestry equipment a higher reliability and increased of its mechanical availability, allowing them to maintain themselves normal operating conditions for the longest time possible, impacting directly on cost reductions as well as operating yields. However, there is a gap between maintenance and operation and a difficulty in measuring the real variables in which maintenance interferes, within the scope of ensuring availability and reliability of equipment for the harvesting operation (Lima, 2019).

Advanced computational methods, such as Artificial Neural Networks (ANN), have been used in the Search for ways to achieve greater assertiveness in decision-making that may influence the performance of equipment, whether in productivity or mechanically. It is a parallel computational system composed of several simple processing elements (artificial neurons) connected among themselves in a specific way to perform a certain task, They are more accurate than other statistical techniques and accept an unlimited number of variables (Peng & Wen, 1999).

Defining the optimal number of neurons in the hidden layer is extremely important, since an excessive number of neurons can lead to the memorization of training data, a process known as overfitting. In na opposite way, when the number of neurons in the hidden layer is small, it may not be enough, a process known as underfitting (Braga et al., 2000; Reis et al., 2019; Almeida et al., 2021).

Considering the contextualized problem, the need to search for alternatives that are able to positively assist in elevation or maintaining the mechanical availability of equipment in the forestry sector, especially mechanized forestry harvesting, becomes of great importance to the process. The main objective of this study was to develop readily available mechanical availability prediction models that can be easily applied.

2. Method

2.1 Study Area

The data from the forest harvesting process were obtained, compiled and organized into a production monitoring database of a forest sector company located in the northern region of the state of Espírito Santo.

The evaluated areas are located in flat to gently undulating relief (with a maximum slope of up to 5%), altitudes between 10 m and 50 m. The climate is tropical Aw classified according to Köppen, with average annual rainfall between 1,350 and 1,375 mm, with the rainy period from October to December and the dry period from July to September, with rainfall irregularities from January to June. In these areas predominate the soils: abrupt yellow argisol A, moderate A planosol or prominent A and quartzarenic neosol (Silva et al., 2014). The data collection period was from September 24th to October 25th, 2020.

2.2 Database

The database with 409 observations contains information from 11 harvesters, 47 operators in rotation of three shifts lasting 8 hours in a period of 31 days, totaling 4,965.33 hours worked, in 08 production units (PU) that varied the useful area from 2.18 to 66.52 ha with 3 types of clones. The average individual volume (AIV) ranged from 0.3050 to 0.3913m3. Data from the forest register (Useful area, Clone, Spacing, Future management, barkless cut volume (VCSC) and from the pre-cut inventory (PCI), PU and AIV) were used.

In this research, the harvesting cut-to-length system and the operation via a forest harvester were analyzed. Such equipment can be defined as a high mobile and stable driving set consisting of a tire, track or mixed base machine, a hydraulic boom and a head. This forest harvester is able to simultaneously perform the operations of felling, delimbing, tracing, debarking and stacking the wood (Machado, 2014).

The model evaluated consists of a hydraulic crawler excavator from Komatsu, model PC200-F, with a model 370E harvester head from the same manufacturer.

To calculate the mechanical availability, the model used by the company was adopted, which can be expressed by the following expression:

2.3 Mechanical Availability

$$MA\ (\%) = \frac{SH - MS}{MS} \times 100 \quad (1)$$

Where, MA (%) = Mechanical availability in %; SH = Scheduled hours; MS = Maintenance hours.

2.4 Networks Used

The trained networks were the Multilayer Perceptron (MLP) type. MLPs consisto f two layers of artificial neurons that process data from intermediate and output layers, in addition to a layer of artificial input neurons (Figure 1). The Neuro version 4.0.6 software was used to obtain the neural networks.

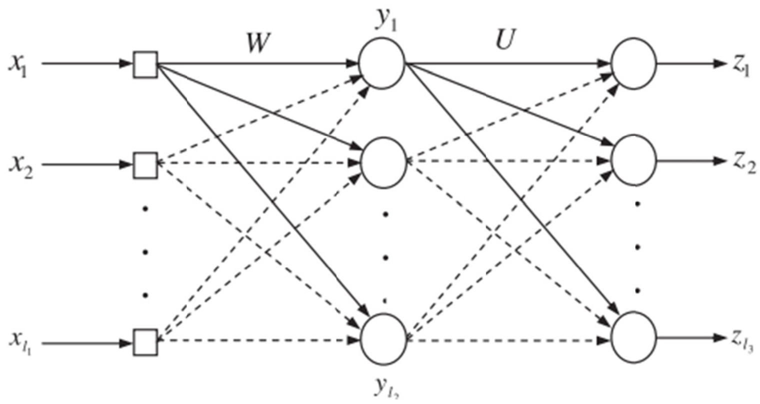

Figure 1. Configuration of MLP network

The networks were trained by alternating the number of neurons in the hidden layer, the training algorithms (Backpropagation, Resilient Propagation and Quick Propagation) and the activation functions (Logistics and Sigmoidal). Fifty networks were trained for each configuration, totaling 3,600 networks.

The stopping criterion used was the number of 3,000 cycles and an average error of 0.0001, therefore, the network training was interrupted when it reached any of these criteria. The networks were selected based on the correlation between the observed and estimated mechanical availability, square root mean square error.

$$\text{RMSE (\%)} = \frac{100}{\overline{\text{DM}}}\sqrt{\frac{\sum_{i=1}^{n}(\text{DMi} - \widehat{\text{DMi}})^2}{n}} \tag{2}$$

$$\text{Erro (\%)} = \frac{(\widehat{\text{MAi}} - \text{MAi})}{\text{Mai}} \times 100 \tag{3}$$

Where, $\overline{\text{DM}}$ is the mean of the total mechanical availability values; n is the total number of observations; DMi is the value of the observed mechanical availability and $\widehat{\text{DMi}}$ is the value of the estimated mechanical availability.

The RMSE assesses the accuracy of the estimate, and the lower the more accurate, and the correlation indicates the degree and direction of the association between estimated and observed mechanical availability.

3. Results

Table 1 presents the descriptive analysis of numerical variables used in the modeling of cutting productivity with harvester in the stands evaluated.

Table 1. Presents the statistical summary of the input variables used to estimate mechanical availability

Input variable	Average	Standard deviation	Minimum	Maximum	Asymmetry	Kurtosis
HW	16.12	4.17	3.27	22.28	-0.90	0.07
MSH	3.72	4.18	0.00	20.60	1.39	1.58
OSH	4.11	2.07	0.11	11.76	1.83	3.72
Goal	81.01	2.43	78.29	86.92	0.87	0.05
PlanPro	495.13	28.67	472.68	636.64	4.32	18.72
ReaPro	498.21	171.61	64.04	842.90	-0.45	-0.53
AIV	0.35	0.02	0.31	0.39	0.13	-0.37
Prod	30.42	5.68	9.84	43.67	-1.02	1.23

Note. HW: hours worked; MSH: mechanical stop hours; OSH: operational stoppage hours; Target: (trees/vg/hours); PlanPro: Planned production (m^3); ReaPro: Realized Production (m^3); AIV: average individual volume; Product: Productivity.

The statistical summary presented is important because the variability of the input data used in the input of information for training and validation of neural networks can define the relevance in terms of synaptic weights of these variables in the model. With the exception of the "goal" and AIV variables that presented a low dispersion of data in relation to their average, 81.01±2.43 trees/vg/hour and 0.35±0.02 m³, the other variables presented a dispersion medium or high, this variability in relation to the average is important to provide greater assertiveness in the configuration of networks and in the models generated.

Table 2. Characteristics and accuracy of artificial neural networks (ANN) selected to estimate the MA (mechanical availability) of mechanized forest harvesting equipment (harvester)

Neurons in the hidden layer	Training algorithim	No. of cycles	Activation function		Training		Validation	
			Training	Validation	R^2	RQME	R^2	RQME
7	Backpropagation	3000	Sigmoidal	Sigmoidal	0.8843	0.0756	0.8402	0.1049
	Resilient propagation	3000	Sigmoidal	Sigmoidal	0.9969	0.0081	0.9993	0.0077
	Quick propagation	3000	Sigmoidal	Sigmoidal	0.9885	0.0248	0.9885	0.0298
8	Backpropagation	3000	Logistics	Logistics	0.8900	0.0746	0.8375	0.1058
	Resilient propagation	3000	Logistics	Logistics	0.9982	0.0086	0.9994	0.0067
	Quick propagation	3000	Logistics	Logistics	0.9895	0.0237	0.9888	0.0300
9	Backpropagation	3000	Logistics	Logistics	0.8881	0.0751	0.8332	0.1070
	Resilient propagation	3000	Sigmoidal	Sigmoidal	0.9985	0.0080	0.9995	0.0065
	Quick propagation	3000	Sigmoidal	Sigmoidal	0.9891	0.0241	0.9904	0.0276
10	Backpropagation	3000	Logistics	Logistics	**0.8911**	**0.0741**	**0.8387**	**0.1054**
	Resilient propagation	3000	Sigmoidal	Sigmoidal	0.9984	0.0083	0.9994	0.0067
	Quick propagation	3000	Logistics	Logistics	**0.9905**	**0.0225**	**0.9902**	**0.0275**
11	Backpropagation	3000	Logistics	Logistics	0.8882	0.0747	0.8348	0.1066
	Resilient propagation	3000	Logistics	Logistics	0.9987	0.0083	0.9995	0.0061
	Quick propagation	3000	Logistics	Logistics	0.9877	0.0257	0.9884	0.0297
12	Backpropagation	3000	Logistics	Logistics	0.8873	0.0753	0.8316	0.1075
	Resilient propagation	3000	Logistics	Logistics	0.9966	0.0082	0.9994	0.0067
	Quick propagation	3000	Logistics	Logistics	0.9888	0.0245	0.9889	0.0290
13	Backpropagation	3000	Sigmoidal	Sigmoidal	0.8869	0.0751	0.8326	0.1073
	Resilient propagation	3000	Logistics	Logistics	**0.9976**	**0.0084**	**0.9996**	**0.0060**
	Quick propagation	3000	Sigmoidal	Sigmoidal	0.9874	0.0259	0.9847	0.0340
14	Backpropagation	3000	Logistics	Logistics	0.8883	0.0746	0.8343	0.1067
	Resilient propagation	3000	Logistics	Logistics	0.9976	0.0082	0.9995	0.0062
	Quick propagation	3000	Logistics	Logistics	0.9881	0.0252	0.9845	0.0343
15	Backpropagation	3000	Logistics	Logistics	0.8891	0.0741	0.8380	0.1056
	Resilient propagation	3000	Logistics	Logistics	0.9963	0.0091	0.9994	0.0067
	Quick propagation	3000	Logistics	Logistics	0.9878	0.0255	0.9855	0.0334
16	Backpropagation	3000	Sigmoidal	Sigmoidal	0.8871	0.0746	0.8355	0.1064
	Resilient propagation	3000	Logistics	Logistics	0.9971	0.0082	0.9995	0.0063
	Quick propagation	3000	Logistics	Logistics	0.9882	0.0251	0.9861	0.0326
17	Backpropagation	3000	Logistics	Logistics	0.8901	0.0742	0.8372	0.1059
	Resilient propagation	3000	Logistics	Logistics	0.9966	0.0086	0.9995	0.0061
	Quick propagation	3000	Logistics	Logistics	0.9864	0.0274	0.9865	0.0328
18	Backpropagation	3000	Logistics	Logistics	0.8908	0.0742	0.8344	0.1067
	Resilient propagation	3000	Logistics	Logistics	0.9980	0.0084	0.9995	0.0061
	Quick propagation	3000	Logistics	Logistics	0.9862	0.0272	0.9868	0.0317
19	Backpropagation	3000	Logistics	Logistics	0.8907	0.0742	0.8369	0.1059
	Resilient propagation	3000	Logistics	Logistics	0.9967	0.0081	0.9994	0.0069
	Quick propagation	3000	Logistics	Logistics	0.9845	0.0287	0.9803	0.0388

The predicted values were very close to the desired values and were uniformly distributed throughout. Although the results of the training phase were generally better than the test phase, there was a trend towards the Resilient Propagation algorithm, where among all the trained ANNs, those that obtained the best R^2 correlation values were contained for this algorithm. This result is similar to that found in mechanical availability assessments for tractors (Rohani et. al 2011).

The graphical analysis of the s-errors and the correlation between observed and estimated values of the network combinations is shown in Figure 2.

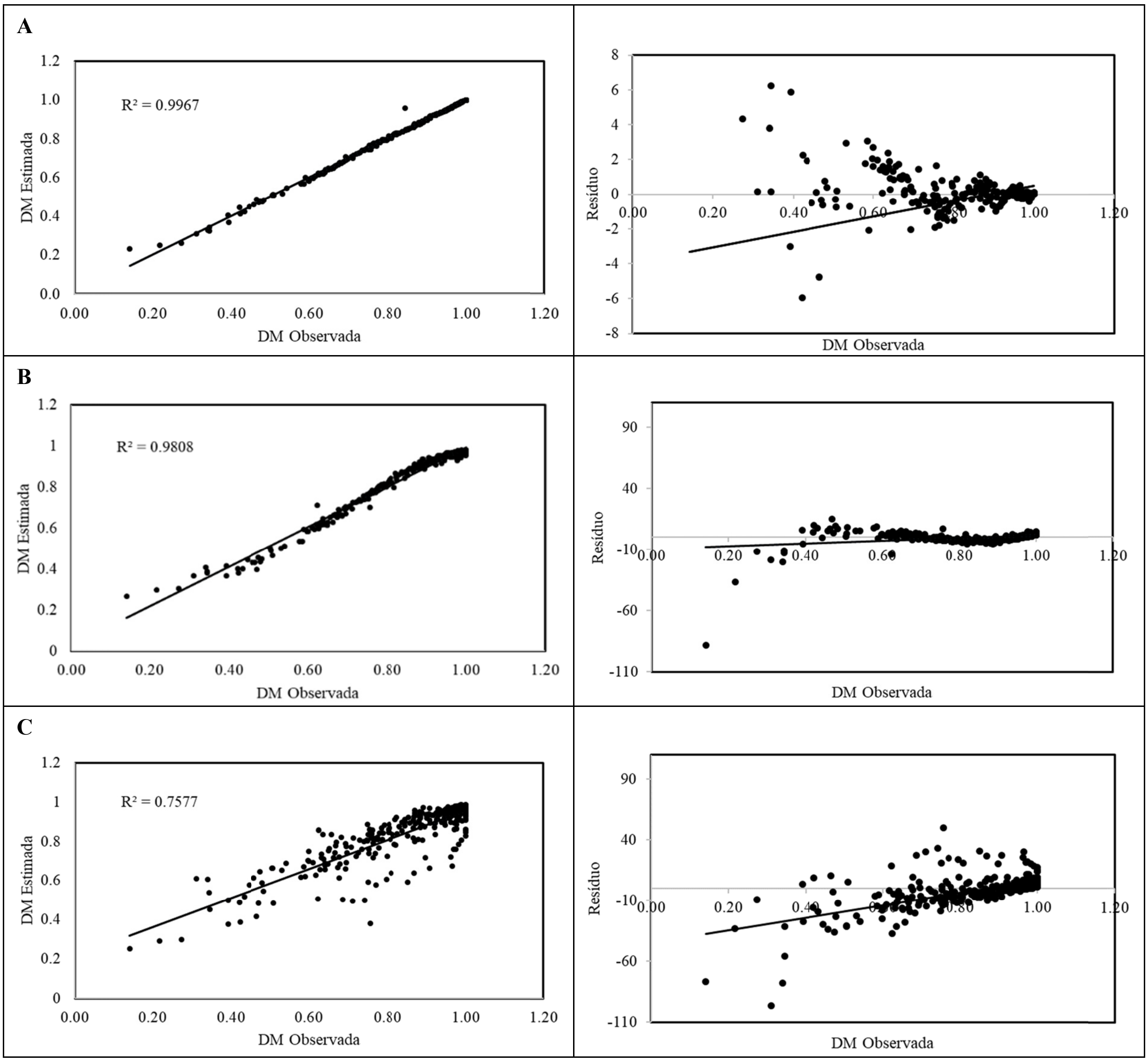

Figure 2. Estimated and observed mechanical availability and error dispersion of neural networks: A) resilient propagation, B) Quickpropation and C) Backpropagation

4. Discussion

The normality of the data, defined by the asymmetry and kurtosis coefficients, is not a definition or choice criterion for the input variables, however, the data distribution can interfere in the synaptic weights of these variables and the network configurations can be adjusted.

During the training phase, the net used the training set until a steady state was reached. Considering the mean values of the action standard deviation and variance, it can be deduced that the values and dispersion taxation of actual and predicted data are analogous. However, the differences in minimum and maximum values are notable. These were probably due to the fact that the extreme values were not well represented in the training dataset, because these were only one or two points.

In the test phase, we use the selected topology with adjusted weights. The objective of this step was to test the network and its generalization properties to assess the competence of the trained network. Therefore, the network was evaluated by data, outside the training set. Table 2 contains some statistical properties of the data used in the testing phase and the corresponding prediction values associated with different training algorithms.

The ANN selected in the training and validation to estimate of mechanical availability, presented correlation coefficient values above 0.89 and RQME values lower than 0.075, indicating a strong correlation and high accuracy between the estimates and the observed values. The ANN configured with 13 neurons in the hidden layer and the "resilient propagation" training algorithm presented the best results of R^2 (0.9905 and 0.09902) and RQME (0.0225 and 0.0275), in training and in validation respectively. These networks were of the MLP type and used all available categorical and numerical input variables. Rohani et al. (2011), Vendruscolo et al. (2015), Reis et al. (2019), and Almeida et al. (2021) in studies related to productivity of agricultural tractors and operations related to forest harvesting found similar configurations, thus estimates close to the observed values, concluded that artificial neural networks can be used to estimate parameters related to forest harvesting.

The resilien propagation training algorithm and quickpropagation presented correlation coefficients between the estimated values and observed values considered high, 0.9967 and 0.9908, respectively. This shows that networks trained with these configurations are reliable. In turn, the Backpropagation training algorithm obtained a lower result, with only 75.77% of the variation of estimated mechanical availability being explained by the observed mechanical availability. The graphs of the reiduals corroborate the results of the correlation graphs, whereas the quickpropagation algorithm showed lower percentage variation of errors.

Although both configurations (resilient propagation and quickpropagation) presented very similar statistical indicators, it is worth mentioning that, differently from the backpropation configuration, data stratification was not used for the training of networks, which is the major variability of ANNs. The possibility of inserting numerical variables with high variability in the adjustment generated accurate results.

Regarding the performance of the statistical criteria for the different configurations, with the use of the configuration with the Backpropagation algorithm, it is remarkable the performance decline, evidenced in the graph by the quality statistics. The difference can be explained by the configuration of the number of neurons in the hidden layer (Martins et al., 2020). Therefore, it is extremely necessary to use a network with the ideal number of neurons in the hidden layer, thus allowing the model to be parsimonious and not generate problems such as overfitting and underfitting (Cunha Neto et al., 2019).

5. Conclusions

It was concluded from the network training that the Resilient Propagation training algorithm, presented the most reliable values according to the trained networks, and from the statistical analysis, it was found that at a 95% confidence level (with p-values greater than 0.9) the actual and predicted test data are similar.

It can be said that the application of artificial neural networks offers a practical solution to the problem of estimating mechanical availability quickly and accurately.

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