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ARTIFICIAL NEURAL NETWORK TECHNIQUE TO ESTIMATE FOREST EXTRACTION WORK CYCLE TIME IN A MOUNTAINOUS SITE

TÉCNICAS DE REDES NEURAIS ARTIFICIAIS PARA ESTIMAR O TEMPO DE CICLO DA EXTRAÇÃO FLORESTAL EM UMA ÁREA MONTANHOSA

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ABSTRACT

Forest harvesting is a complex activity, involving the movement of machines and wood volume being affected by several variables that interfere directly or indirectly in this forest operation. Linear models can be used to evaluate the impact of some of these variables on forest harvesting, although linear models have some limitations that prevent a better inference, for this reason, other alternatives such as artificial neural networks (ANN) can contribute to the understanding of the effect of variables on harvesting operations. The objective of this study was to compare the estimates of operational cycle time and the cycle elements in the extraction activity with a tractor winch in mountainous regions. Linear models were adjusted for each of the eight cycles evaluated (7 work steps and work cycle) in addition to seven neural network architectures for each cycle, totaling 56 trained architectures. The results show that the best neural networks trained for each work step presented superior adjustment statistics compared to linear models. In addition to superior results, the ANN presented normal residuals in most cases, a situation not achieved by linear models.

KEYWORDS: **Farm tractor, Forest harvesting, Forest operations, Winching extraction.**

RESUMO

A extração florestal é uma atividade complexa, envolvendo a movimentação de máquinas e volume de madeira sendo afetada por diversas variáveis, que interferem direta ou indiretamente nessa operação da colheita florestal. Modelos lineares podem ser utilizados para se avaliar o impacto de algumas dessas variáveis na colheita florestal, apesar disso modelos lineares apresentam algumas limitações que impedem uma melhor inferência, para isso outras alternativas como redes neurais artificias (RNA) podem vir a contribuir para compreensão do efeito das variáveis nas operações de colheita. O objetivo do presente estudo foi comparar as estimativas de tempo do ciclo operacional e os elementos do ciclo na atividade de extração com trator guincho em regiões montanhosas. Foram ajustados modelos lineares para cada um dos oito ciclos avaliados (7 etapas do ciclo e ciclo operacional) além de sete arquiteturas de redes neurais para cada ciclo, totalizando 56 arquiteturas treinadas. Os resultados encontrados apontam que as melhores redes neurais treinadas para cada ciclo apresentaram superioridade nas estatísticas de ajuste em relação aos modelos lineares. Além de resultados superiores, as redes neurais apresentaram resíduos normais na maior parte dos casos, situação não atingida pelos modelos lineares.

PALAVRAS-CHAVE: **Colheita florestal, Extração por guinchamento, Operações florestais, Trator agrícola.**

INTRODUCTION

Forest harvesting on sloping terrain is an activity that presents a challenge in terms of economic feasibility, safety, and environmental impacts (Tsioras et al., 2011; Visser & Stampfer, 2015). Modern forestry machines that mechanize the entire harvesting process are an option that still suffer from sloping terrain limitations (Alam et al., 2013; Strandgard et al., 2014). From harvesting activities, greater attention is paid to forest extraction according to Lopes et al. (2007) present greater complexity and numerous factors that affect this operation. Despite the many benefits, the investment required to acquire forestry machinery discourages mainly small producers (Spinelli & Magagnotti, 2012). The use of agricultural tractors is an alternative of low initial cost, easy operation and ,satisfactory production (Mousavi & Nikooy, 2014), in addition to being versatile, being able to work in different terrains and forest stands with low and medium individual volume. (Gilanipoor et al., 2012).

Many variables can affect the activity of a forest machine, according to Malinovski et al. (2006) these can be distinguished between variables of immediate or indirect identification. Volume to be extracted, topography, area extension, forest species, road density, soil type, rainfall, and average distance of extraction, among others, are of identification. Others such as skill and availability of labor, risks of soil compaction, restrictions imposed by forest management, and machine stability in sloping areas are examples of variables of determination, still according to the same authors.

In many cases, these variables do not show a linear relationship with the time of a forest extraction work cycle, or with its productivity (Gonçalves et al., 2021). This characteristic makes the use of linear models inappropriate in forest harvesting. An alternative to linear models is the use of machine learning, including the method of artificial neural networks. Although machine learning techniques have shown efficiency in other forest applications (Vieira et al., 2018; Martins Silva et al., 2019) there are still few studies on its application in forest harvesting (Gonçalves et al., 2021) especially in forest extraction in mountainous regions.

Based on the above, it is questioned whether the application of artificial neural networks in the prediction of the work cycle and work steps time can generate better results than more common linear models. Because of this, the present study aims to compare artificial neural networks and linear models regarding their ability to generate predictions of the duration of the work cycle and work steps, in addition to evaluating the influence of predictor variables on work times.

MATERIAL AND METHODS

Study area

The study was conducted in the clear-cut areas of a forestry company located in the southern region of Brazil, in the municipalities of Itaperuçu and Rio Branco do Sul, between coordinates 25º09'S and 49º19'W (Figure 1). The topography of the area is/was classified as undulating to mountainous (EMBRAPA, 2018), with slopes ranging from 20 to 75%. The region has a Cfb climate, temperate climate with mild summers, according to the Köppen classification. (Alvares et al., 2013).

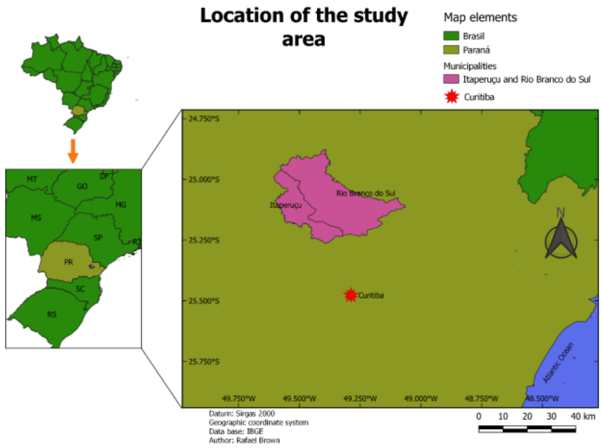

Figure 1. Study area location

Logging operation description

The clear-cut operations took place in a 16-year-old *Pinus taeda* L. plantation. The plantation had a density of 563 trees ha^{-1} and an average individual volume of 0.6 m^3. The harvesting method adopted by the company was that of whole trees, which were later processed at the edge of the field by a harvester head. In the harvesting system adopted by the company, the felling of trees was carried out in a semi-mechanized way, with the chainsaw operators directing the fall of the trees in the direction favorable to the slope.

The extraction was carried out in a mechanized way using an adapted agricultural tractor with a winch in its rear power take-off. A Valtra brand agricultural tractor with 600-900 hours of use, 96.7 kW of power at 2300 RPM coupled to a TMO winch with 323.6 kN traction and 19 mm thick steel cables were used in the extraction operation. The extraction team consisted of two employees, a tractor operator, responsible for the operation of moving the tractor and driving the winch, and a choker setter, responsible for pulling the winch cable to the point where the trees that would be extracted were, tying the chains on the trees and then removing the chains from the trees in the log yard.

In this study, the tree extraction work cycle was divided into seven work steps (Table Z), as proposed by Spinelli & Magagnotti (2012) and Proto et al. (2018). A total of 87 operational cycles of wood extraction made up the database and all were composed of the seven partial elements of the operation. In addition to measured times, winching distance, skidding distance, and winching slope were also measured.

Empty travel (TE): starts when the tractor leaves the site and ends with its arrival at the winching location.

Cable pulling (CP): starts when the choker setter grabs the cable hook of the winch line and ends when he arrives at the trees to be winched

Hook load (HL): starts with the passing of the chokers around the trees to be winched and end with a signal from the choker setter.

Winching load (WL): starts the moment the winch draws the load to the tractor awaiting by the road and ends when the turn (group of attached logs or trees) reaches the road. The distance between the trees in the field and the tractor was considered the winching distance.

Loaded travel (TL): starts once the trees are off the ground (on one end) and ends when the tractor arrives at the landing. The distance between where the choker chains were wrapped, and the landing was considered the skidding distance. The sum between winching distance and loaded travel was considered the total extraction distance.

Unhook load (UL): starts when the tractor arrives at the landing, the unhooking process ends when the choker setter places all chokers on top of the winch of the tractor.

Log decking (LD): begins with the unprocessed trees left on the site and ends after they are processed into logs and properly positioned and stacked by the excavator grapples for transportation to the sawmill.

Statistical analysis

First, descriptive statistics of the predictor and predicted variables were performed. In addition, the relationship between the variables was analyzed using Kendall's nonparametric test, as a linear relationship between the variables was not expected.

Modeling

Artificial neural networks

Supervised artificial neural networks, with non-recurring and multilayer architecture were used to model the work cycle, empty travel, cable pulling, hook load, winching load, loaded travel, unhook load, and log decking. In this process, the stochastic gradient descent algorithm with error backpropagation, implemented in the h2o.deeplearning function of the h2o () package in the program/environment R (), was used to update the synaptic weights and biases,

In all ANNs trained, the quantitative variables winching distance, skidding distance, and slope were used in the input layer in a standardized scale. To define the range of neurons tested in the single hidden layer, the Fletcher-Gloss method (Eq. 1), described by Silva et al. (2010), was used. In this layer, the hyperbolic tangent function was the only one tested and, in the output layer, the linear activation function was used.

$$2 \cdot k^{0.5} + n_2 \leq n_1 \leq 2 \cdot k + 1 \quad (1)$$

In which:

k = number of input variables in the network

n2 = number of output layers

n1 = number of neurons in the input layer

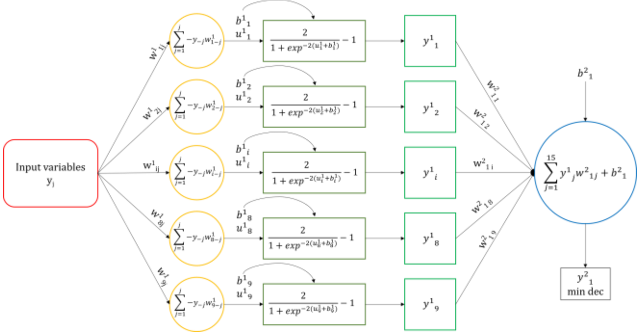

Figure 2. General structure of an ANN with nine neurons at hidden layer

Finally, by combining all the hyperparameters tested, seven ANNs were trained to model each of the predicted variables, totaling 56 trained networks. When the ANN with the highest number of neurons in the hidden layer presented the best performance, additional ANNs were trained with the gradual addition of one neuron in this layer, at a time, up to the limit of 10 neurons.

Generalized linear model

Equally in the ANNs modeling, the h2o package was used to adjust the GLMs, but with the h2o.glm function. To model all variables, the Gaussian distribution family together with the identity binding function, its canonical, were used. To estimate the coefficients, the iteratively reweighted least squares method, explained in Rubin (2006), was used.

$$\hat{y} = \beta_0 + \beta_1 \cdot WD + \beta_2 \cdot SD + \beta_3 \cdot SL \quad (2)$$

In which:

ŷ = estimated variable

βi = estimated parameters

WD = winching distance

SD = skidding distance

SL = slope

Goodness-of-fit

To assess the accuracy of generalization to new data, the k-fold cross-validation method was used in the modeling process of both techniques. The database was randomly divided into 4 subsets and, for the calculation of precision measures (Eq. 3, 4, 5 and 6), the predictions for each of the four folds were combined into a single set.

$$NRMSE = \frac{\sqrt{\frac{100}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{\underline{y}} \quad (3)$$

$$MAE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n} \quad (4)$$

$$Bias\ \% = \frac{\sum_{i=1}^{n}\left(\frac{\hat{y}_i - y_i}{y_i}\right)}{n} \cdot 100 \quad (5)$$

$$RSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y_i}\right)^2} \quad (6)$$

In which:

NRMSE = normalized root mean square error

MAE = mean absolute error

Bias % = percent bias

RSE = relative standard error

yi = observed value y

ŷi = estimated value y

ȳ = mean of y

n = number of observations

In addition to these measurements, the normality of the prediction residuals was evaluated by the Kolmogorov-Smirinov test and by the graphical analysis of the residuals. The importance of each variable in the modeling was also evaluated. For the ANNs, the method proposed by Gedeon (1997) was used and, relating to generalized linear models, the values of the coefficients estimated in a standardized scale were used (Elashoff et al., 1975; Nathans et al., 2012).

RESULTS

Descriptive statistics

Table 1 presents the descriptive statistics of the predictor variables, the work steps, and the work cycle observed in the field.

Table 1. Descriptive statistics

Variable	Unit	Mean	Max	Min	Sd	SEM	CV (%)
Winching distance	meter	81.95	135.61	6.29	32.46	3.48	39.61
Skidding distance		66.39	241.82	4.66	64.22	6.88	96.73
Slope	degree	23.52	36.4	13.05	6.62	0.71	28.13
Empty travel	min dec.	1.46	3.15	0.15	0.66	0.07	45.21
Cable pulling		1.47	4.28	0.23	0.84	0.09	57.12
Hook load		3.92	9.62	0.81	1.64	0.18	41.83
Winching load		3.80	8.09	0.8	1.63	0.17	42.93
Loaded travel		1.48	6.00	0.18	1.11	0.12	74.99
Unhook load		1.53	4.11	0.41	0.79	0.08	51.76
Log decking		1.42	4.23	0.6	0.61	0.06	42.67
Work cycle		15.08	27.31	6.7	3.55	0.38	25.56

In Figure 3 it is possible to observe the Kendel correlations between the predicted and predictive variables, as well as verify their distribution and whether there is a linear relationship between them. In addition to the value of Kendall's correlation, it is possible to verify the distribution. At the bottom, graphs are plotted to verify the linear relationship between the variables.

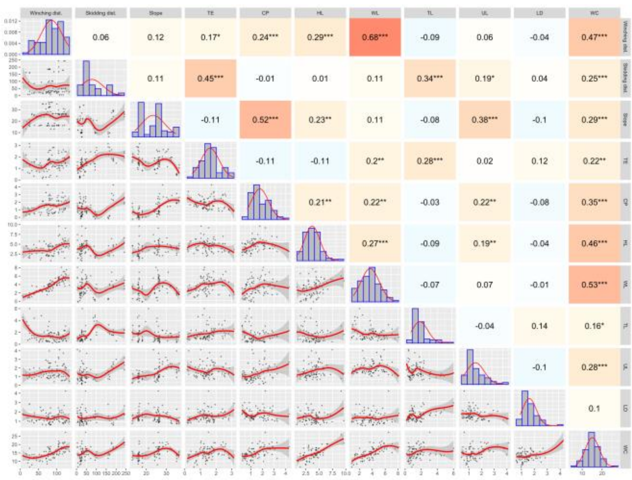

Figure 3. Variables correlation matrix

Figure 4 underneath presents a box plot chart with the percentage composition of the work cycle, in red, possible outliers, and in orange the observed average. The choice of the boxplot chart was due to the observable variation in the composition of the work steps in the work cycle under different conditions of distance and slope. A greater number of possible outliers can be observed in the empty travel and loaded travel work steps, possibly due to a greater variance in the skidding distance variable, precisely the variable most correlated to these two work steps.

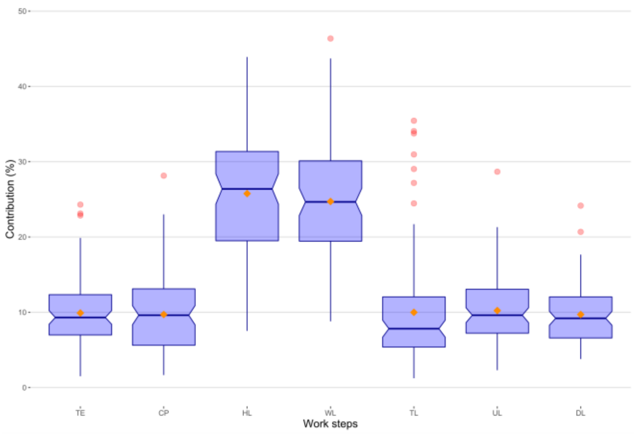

Figure 4. Percentage composition of the work cycle elements of the agricultural tractor with winch.

After verifying the descriptive statistics and correlation between the variables, the GLM adjustments and neural networks training were then performed. Figure 5 presents the contribution of each predictor variable in the adjustment for each work step evaluated. It is important to highlight that the techniques to calculate the importance of these variables are different between the GLM and the ANN, so the interpretation of the most important variables must be given in the order of importance and not in their relative importance value.

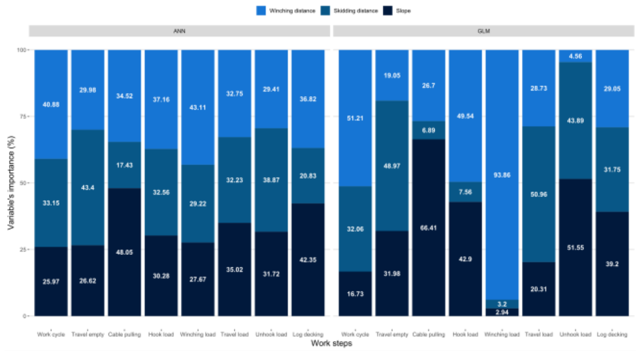

Figure 5. Variables importance

In addition to the importance of the variables, the statistics below also allow us to compare the quality of the prediction of the best ANN architectures with the generalized linear models for the work cycle and the seven work steps. We can observe that despite the adjustment statistics being close in the two techniques, the ANN showed superiority in addition to the fact of generating normalized residues.

Table 2. Statistics of goodness-of-fit

Work step	Model/Topology	NRMSE	MAE	Bias (%)	Cor	RSE	KS stat
Work cycle	ANN 3-8-1	14.98	1.6536	2.31	0.7377	1.0272	0.0716
	GLM	15.41	1.7216	2.85	0.7159	0.9159	0.9883*
Empty travel	ANN 3-9-1	30.62	0.3373	21.47	0.7346	1.0209	0.0920
	GLM	31.3	0.3438	18.08	0.7193	0.8333	0.0966*
Cable pulling	ANN 3-5-1	37.83	0.4308	22.77	0.7205	1.0287	0.0727
	GLM	38.31	0.4194	16.7	0.7129	0.8602	0.1251**
Hook load	ANN 3-9-1	34.47	1.0509	17.00	0.3849	6.4895	0.0662
	GLM	35.87	1.0906	16.77	0.3128	4.4273	0.0643
Winching load	ANN 3-10-1	23.56	0.697	7.81	0.8356	0.5005	0.0868
	GLM	24.49	0.694	5.90	0.8194	0.4635	0.0703
Load travel	ANN 3-5-1	57.55	0.583	36.70	0.5131	2.7141	0.1430**
	GLM	59.03	0.6082	42.63	0.4777	2.6763	0.1263**
Unhook load	ANN 3-9-1	36.49	0.4059	14.85	0.6386	1.874	0.0873
	GLM	36.51	0.4132	13.52	0.6338	1.4512	0.0951
Log decking	ANN 3-5-1	37.16	0.4048	13.27	0.1997	10.8875	0.1418**
	GLM	38.91	0.4272	14.94	0.0097	18.2961	0.1362**

Figure 6 presents the scalar residues of the fitted linear model (blue) and the training of ANN (red) in all work steps of winching trees.

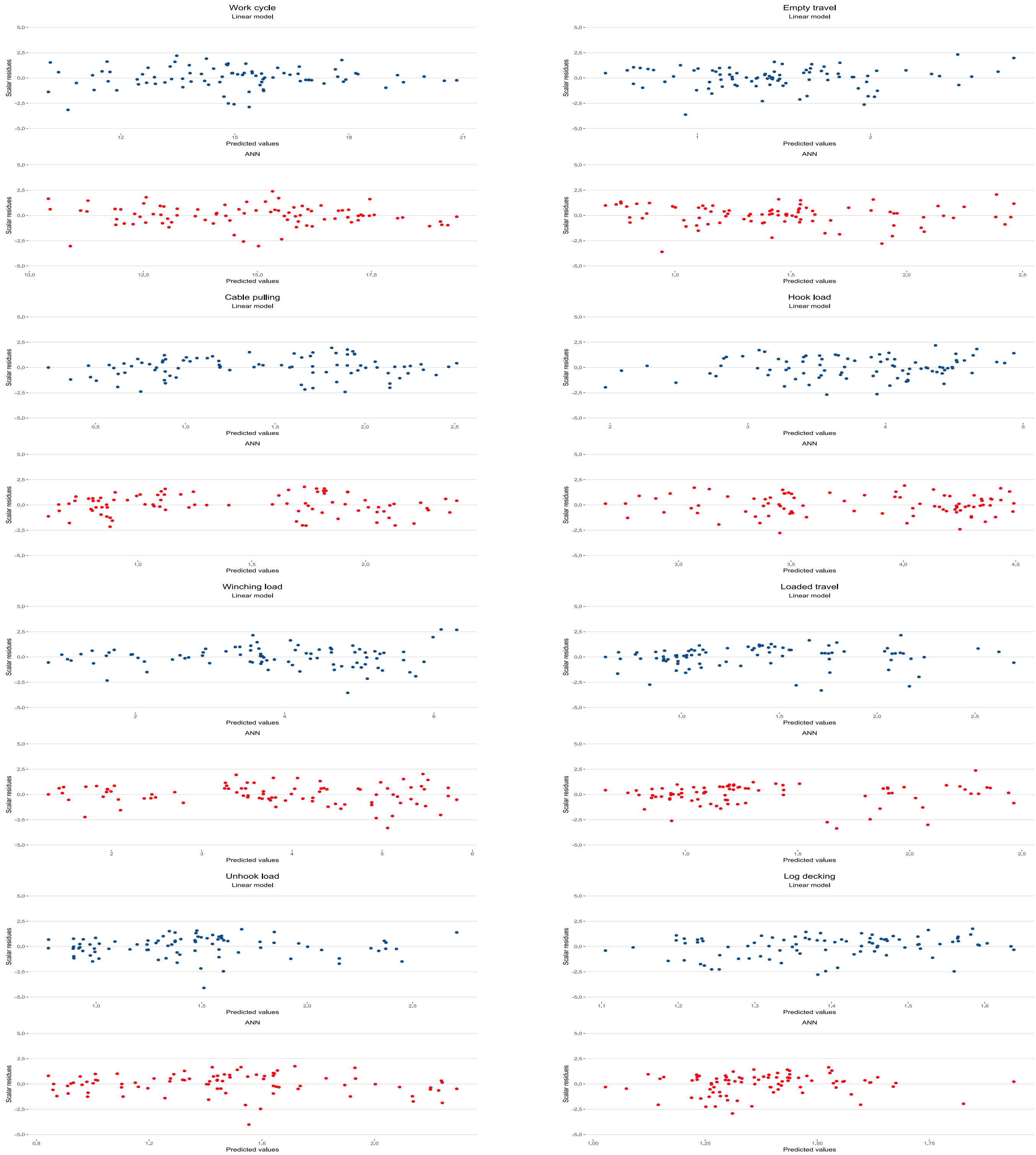

Figure 6. Scalar residues

As can be noticed, both techniques present a good result with well-distributed residues.

DISCUSSION

When observing the contribution of the work steps in the composition of the work cycle, one can observe the predominance of two work steps, hook load (25.77%) and winching load (24.71%). The hook load is an element that develops entirely from the physical effort of the choker setter inside the field in a condition of slope, residue of branches and needles, stumps, among other obstacles. In this work step, the choker setter needs to choose which trees will be extracted in that work cycle and pass the chains under them in places that are often difficult to access. These characteristics of this work step end up demanding time and physical effort from the worker, which would explain the greater spent time. In a study using a choker skidder, Lopes & Diniz (2015) found values of 46.67% (considering cable pulling and hook load), compared to 35.48% in this work if we consider the two elements together. Proto et al. (2018) found values of approximately 20.50% in these work steps, even having extracted on average a greater number of trees and a greater volume. Borz et al. (2013) in turn found values of 12-16%, but in conditions of greater drag distance, which makes the hook load element less representative.

In the winching load work step, greater differences were observed between this work and others, such as found by Lopes & Diniz (2015) with 8.33%, 41-43% (Borz et al., 2013), Çağlar (2021) 49.2% and Gulci (2020) 49%. In the work by Proto et al. (2018), values were found close (21.9%) to those observed in this work. This difference can be explained by the traction capacity of the winch used in the work by Lopes & Diniz (2015), who observed a winch with a traction capacity of 183.5 kN compared to the 326.6 kN of the winch in this work. Another important factor was that the maximum length of the cable used in the skidder choker was 110 meters, operating at lower winching distances than those found in this work. This suggests the importance of sizing the winch and its pulling capacity that could optimize the work cycle times since the pulling capacity is inverse to the cable pulling speed.

The other less representative work steps were the following: empty travel (9.91%), cable pulling (9.71%), loaded travel (9.99%), unhook load (10.23%) and log decking (9.70%). An alternative to using chains would be the use of slings with sliding couplings that could reduce hook and unhook load times. The use of skidding cones could also allow a reduction in time and even events such as cable breaks, making winching load faster and safer. These are some examples of devices that could make extraction with a winch faster, without having to change extraction variables such as winch distance, drag distance and slope, which are variables that are less likely to be changed.

Observing the descriptive statistics, firstly a characteristic of the input variables of the models, the skidding distance draws attention because the maximum and minimum values are quite discrepant. Although the average of the skidding distance is smaller than the winching distance, the deviation of the values is greater in the first one. These values express a characteristic in the harvesting operations in mountainous regions observed in this study, the scarcity of adequate spaces for the construction of log yards due to the greater slopes resulting in smaller amounts of flat areas capable of storing the volume of wood to be extracted. Due to the difficulty of building patios close to the extraction area, in some cycles it was necessary for the tractor to drag the trees for distances greater than 100 meters in order to place them in a suitable patio.

It is possible to notice from the correlation matrix that the work steps: empty travel, loaded travel and to a lesser extent the unhook load were influenced by the drag distance. The unhook load element stands out here, where the drag distance has an influence may be due to the fact that this work step is performed by the choker setter. That is to say, the choker setter covered the entire dragging distance on foot, after climbing the hill to then perform the unhook load, and these great distances can even impact a work step performed inside a log yard.

The slope, in turn, affects mainly the work steps where the activities were entirely performed by the choker setter, suggesting that the slope is a variable that, despite impacting the work cycle, affects less the tractor and more when human physical effort is employed. This fact is evidenced when evaluating in the correlation matrix that the slope variable affected cable pulling, hook load and unhook load. Unhook load can be affected for the same reason that the drag distance affects it, as it requires the choker setter to travel the distance after climbing the hill and being influenced by the slope of the field. In this case where the slope proves to be a challenge for the choker setter, a winch cable unwinding system and a return cable could make extraction more productive.

Finally, the variable most related to the times spent in the work steps and in the work cycle is the winching distance, which mainly affects the winching load, with the correlation matrix even demonstrating a good linear relationship between the two variables.

When comparing the adjustments of the linear models, the training results in the different architectures of neural networks and the correlation matrix, it is possible to evaluate the predictor variables that contributed most in each work step and in the work cycle.

When estimating the work cycle time, it was observed that both in the neural network, and especially in the linear model, the slope variable proved to be the variable with the smallest contribution to the adjustments. Despite this, in the correlation matrix, it presents a greater correlation than the skidding distance. Much of the slope influence can be attributed precisely to its influence on the hook load, which was the most representative work step in the work cycle. This result initially suggests that operations with agricultural tractors and winch are a good option for logging in mountainous regions, and this operation is little affected by the slope variation typical of mountainous regions. The predictions of the work cycle times had better results with the neural networks, which presented better statistics of their performance compared to the linear model. Neural networks also generated residuals with normal distribution, unlike the linear model.

When evaluating the elements separately, the importance of the predictor variables changed, due to the fact that each work step occurs in different locations, being processes different from each other, with different factors that affect each one of them. The best adjustment results were obtained in the work steps: empty travel, cable pulling, winching load, and unhook load. The hook load, loaded travel and log decking elements presented the worst results.

In empty travel, the most important variable was the skidding distance, which is the distance that the tractor travels from the shipyard to the point where it will winch trees. The importance of the skidding distance can be observed both in the correlation matrix and in the importance values of the linear model and in the neural network. The linear model in this element showed good values in the fit statistics, despite that the residuals did not show normality, unlike the neural networks that also had good performance in the predictions and normal residuals.

Cable pulling is an element of the cycle where the choker setter needs to pull the cable from the tractor winch to the point where the trees to be winched are, although the winching distance has a smaller influence on the execution time of this activity than the slope. This can be observed in the value of the importance of the slope variable in the linear model and in the neural network. In the prediction statistics, both the neural networks and the linear model present themselves as good strategies for predicting the time of this element, despite this, only the neural networks showed normality in the residuals.

Inversely to cable pulling, the winching load is performed by bringing the trees from the point where they were tied to the agricultural tractor, in this work step, which together with the hook load is one of the steps that most contribute to the work cycle time. The winch distance is the most related variable and has significance in the linear model and importance when training neural networks. Drag distance and slope are non-significant variables in the adjustment of the linear model, and are of low importance in the training of neural networks. Both the neural network and the linear model presented similar performance in the predictions of this cycle, with low errors, good correlation between the predicted and observed values, in addition to normality in the residuals. In this work step the best neural network presented ten neurons in the hidden layer, this suggests that the addition of more neurons can bring a better performance.

In unhook load, the most correlated variable is the slope of the terrain, despite being an activity carried out inside a log yard, therefore in an environment not affected by the slope of the plot. In the linear model, the slope variable presented the greatest importance, while in the neural network, the greatest importance was given to the skidding distance. The linear model adjustment and the trained neural networks presented good performance, although inferior to the elements discussed above. Regarding the normality of the residuals, it was observed in the trained neural network and in the linear model.

The work steps, hook load, loaded travel and log decking were the elements where the worst predictions were observed in the evaluated techniques. The hook load is an activity that takes place entirely within the field, empirically it is not verified that the skidding distance or the winching distance would have any effect on this activity, in which case the difficulty encountered by the operator in passing the chains underneath the trees is more relevant, in addition to the distance between the trees to be extracted. The slope would also have an effect on this activity since the displacement of the choker setter is done in the slope conditions, this can be observed in the importance of the slope in the linear model, despite this, in the training of neural networks slope was the least important variable. Even so, the neural networks showed a small superiority in relation to the linear model.

The loaded travel activity takes place entirely within the road, between the winch point of the trees to the shipyard where they were stored, this distance between these two points comprised the skidding distance. It is expected that this variable is the most relevant when predicting the loaded travel time, this was observed in the importance value in the linear model, in the neural network it was the variable with the least importance in training. Despite this, the neural networks presented smaller errors when compared to the linear model, but none of the strategies presented normality in the residuals.

In log decking, no predictor variable was presented as a good alternative, it is justified that it is an activity that takes place in a location where no variable has an influence because it is carried out entirely within a log yard where no measurements of the yards were obtained. Because of this, it was also the element of the cycle that presented the worst results in the predictions, both with neural networks and with the linear model. In addition to higher errors, predicted values showed low correlation with observed values and non-normal residuals in all chosen strategies.

Despite satisfactory results, it was clear that to adjust the work steps separately, both with linear models and with neural networks, it is necessary to evaluate them as a separate process step, with their distinct characteristics and predictor variables that influence each of the work steps in a particular way. When evaluating the work cycle, the neural network presented good results, being a good alternative in the evaluation and prediction of the work cycle time. Currently, more forestry equipment is equipped with sensors enabling telemetry at different moments of forest harvesting in real time. Machine learning, including neural networks, will be able to play an important role in the planning, control, and simulation of harvesting operations (Piragnolo et al., 2019; Maktoubian et al., 2021) seeking more productive processes as well as alternatives for forestry operations with less environmental impact.

CONCLUSIONS

The winch distance variable was the most influential variable and therefore the best variable to estimate the work cycle time and most work cycle elements.

Drag distance has an influence when evaluating the work cycle, unlike the slope. Despite this, both variables have influence when evaluating the elements separately.

The total work cycle and the elements: empty travel, cable pulling, winching load and unhook load showed the best results, with good predictions, lower errors, and normal residuals.

The hook load, travel loaded, and log decking elements presented predictions with high error, tendency, considering them as having unsatisfactory adjustments.

The training of neural networks presented itself as an interesting alternative in relation to the traditional technique of linear model, having generally presented better results than the adjustment of linear models, especially when the normality of the residuals is observed.

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