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Estimation of Total Volume of *Eucalyptus* Through Measurements at the Tree Base

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ABSTRACT

The aim of this work was to estimate the total volume of trees basing on variables measured up to 2 meters in height on the tree and total height, using artificial neural networks. The data used came from 3,620 felled and cubed trees. The input variables used were: input 1 (*DBH*, total height, diameters at 0.00, 0.50, 1.00, 1.50, and 2.00 meters tall); input 2 (addiction of the volume up to 2 meters); input 3 (addiction of the slenderness degree) and input 4 (addiction of the categorical variable representing the form of the stem up to 2 meters tall). The 5 best networks by groups of input variables were retained. The data were divided in 60% for training, 20% for testing and 20% for generalization. To evaluate the quality of the estimates were used the statistics bias, root mean square error, Pearson's correlation and graphical analysis of the residues. The network that presented the best estimations was applied to the independent data to evaluate the capability of this network to estimate volumes for data from different conditions from which it was generated. The best methodology to generate the networks was also applied to independent data to evaluate the quality of the volume estimations. The estimations created with the best network to the independent data presented a strong tendency of super estimation of the volume to smaller trees, evidencing a low development when used to predict volumes of independent data. The networks that provided the best estimations were generated by the input variables 2 (*DBH*, total height, diameter at 0.00, 0.50, 1.00, 1.50, 2.00 meters tall and volume up to 2 meters) group.

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INTRODUCTION

Knowing the amount of wood in forest population is a necessary and fundamental step to all the company, because it is from the information of this production that decisions of forest planning are made. To Davis and Johnson (1987), it is essential that the companies generate current and future volume estimations aiming the correct planning of their activities.

In the process of forest population volume quantification, normally, the performance of forest inventory is needed which consists in measuring part of the population, and then extrapolate the results to total area (Leite and Andrade, 2002). Thinking of individual trees, volume or taper equations are used, and to be generated felled trees or still standing trees cubage data are used (Oliveira *et al*., 2009). Campos and Leite (2013), comment that the volume equations used must be specific per species, spacing, age and cut regime and the scaling data frequency must be directly related to the diameter and form variation of the population trees. However Guimaraes and Leite (1996), show that to some situations the number of trees needed to adjust a model of volume can vary from 100 to 150.

In practical terms, forest companies present a varied number of genetic matters and the obtaining of scaling data to generate specific equations is extremely onerous. Aiming to overcome the situation, the companies decide to generate specific equations for more representative clones and generic equations to estimate the volume of the others,

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however this practice could result in loss of precision in the generated estimations.

In front of this situation, some methodologies were developed in order to optimize the cubage and volume determination procedure of trees, having as example, the relative height method (Leite and Andrade, 2004), the profiles similarity method (Oliveira *et al*., 2009), and others.

More recently, according to the works of Gorgens *et al*., (2009) and Silva *et al*., (2009), the artificial neural networks (ANN) can also be used to very precisely estimate the volume of trees. Binoti *et al*., (2014), showed that it is possible to estimate the volume of trees through neural networks based in diameter measures at 1.30 m (*DBH*), up to the height of 4 meters and total height, however to perform measurements in big heights on the field is very complicated, what can make the use of this methodology unfeasible.

Artificial neural networks (ANN) are a type of artificial intelligence system similar to the human brain, computing capable to acquire acknowledgement. They can be used in the classification of data, weather series analysis, regression or pattern recognition. The architecture of an artificial neural network refers to how the neurons are organized, where the MLP (Multiplayer Perceptron) is the most used architecture for the prediction of continuous variables (Castro *et al*., 2013) and it is also the most used one in forest handling studies.

Thus this work aimed to estimate the total volume of trees based in variables measured up to 2 meters tall on the tree and total height, using artificial neural networks.

MATERIAL AND METHODS

The data used in this work were obtained from populations of *Eucalyptus* sp., belonging to a company located in southern Bahia, Brazil. The data are from 3,620 felled and cubed trees. The diameters along the stem were measured in the positions of 0.00, 0.50, 1.00, 1.50 and 2.00 m, and from the 2 meters, the sections were measured from 2 m to 2 m up to the tree total height. The data were distributed in six spacings (3.00 x 3.00, 3.50 x 2.57, 3.50 x 2.90, 4.00 x 2.75, 4.00 x 3.00, 5.00 x 2.40), 15 genetic matters (clone) and the ages vary from 2.71 to 11.00 years.

Dispersion graphics were built in order to verify the presence of outliers, accordingly to Draper and Smith (1998), that when confirmed were ruled out from the adjustments.

The input variables used to estimate the trees total volume were: *DBH*, the diameters with bark along the stem, at the positions 0.0, 0.5, 1.0, 1.5 and 2.0 meters, the total height (*Ht*), the tree volume up to 2 meters tall (V2), slenderness degree and a categorical variable representing the form of the stem up to 2 meters. These variables were combined to generate the four input variable groups, wherein input 1 (*DBH*, total height, diameters at 0.00, 0.50, 1.00, 1.50, and 2.00 meters tall); input 2 (addiction of the volume up to 2 meters); input 3 (addiction of the slenderness degree) and input 4 (addiction of the categorical variable representing the form of the stem up to 2 meters tall).

To calculate the total volume of the trees, the method of Smalian was applied and to calculate the volume up to 2 meters of height, the Newton method was applied which could be considered more precise to calculate trunk parts volume (Hush *et al*., 2003).

The slenderness degree (*S*) was calculated accordingly to Wink *et al*., (2012):

$$S = \frac{Ht}{DBH}$$

The categorical variable form of the stem up to 2 meters could assume four different forms:

Parabolic (*PA*), conical (*CO*), cylindrical (*CI*) and "neiloide" (*NE*). To qualify the stem form of the trees, the subtraction of the volume values obtained by the Newton method and the volume of perfect solids, the stem form was then qualified as the solid one that presented lower absolute value in the subtraction. The formulas to calculate the volume of the solid ones used were extracted from Husch *et al*., (2003):

- Parabolic: $V = \frac{1}{2}\left(A_b * H\right)$
- Conical: $V = \frac{1}{3}\left(A_b * H\right)$
- Cylindrical: $V = A_b * H$
- "Neiloide": $V = \frac{1}{4}\left(A_b * H\right)$

in whish: *V*: is volume, m³; A_b: basis sectional area, in m², *H*: is the height, equivalent at 2m.

To ANN training, the data used were divided in three groups, in which: 60% of the data were designed to the training of the networks (2172 trees), 20% (724) to testing and 20% (724 trees) to generalization. The trained networks were MLP type (Multilayer Perceptron) and the data processing was performed through the Statistica 10.0 software (Statsoft, 2010).

For each input variables group 100 neural networks were generated, with neurons number in the processing layer ranging from 1 to 10, and among them the five ones that presented better development at the data estimations designed to generalization.

To select the best ANN, we adopted the stability criteria of the networks training indices generated by the software in the phases of training (ANN creation), selection (training break) and generalization (application of a non-used data group in the training), accordingly to Binoti (2012).

The estimations generated during the generalization phase with the best five networks for each group of input variables were evaluated through the statistics bias (*B*), the root mean square error (RMSE), Pearson's correlation ($r_{\hat{v}v}$) among the observed and the estimated volumes in the generalization for each network, in the percentage errors and frequency histogram of the percentage errors (Campos and Leite, 2013).

For validation, the network that presented the best estimations was applied to independent data to evaluate the capability of it to estimate volumes for data coming from different conditions from which it was generated.

The data used in the validation come from 1,556 felled and cubed *Eucalyptus* sp. trees, collected from a company located in Jequitinhonha Valley – Minas Gerais, Brazil, represented by 13 clones and six spacings (3.00 x 3.00, 3.00 x 2.00, 3.00 x 2.50, 3.00 x 1.70, 3.00 x 2.85, 3.00 x 1.50).

The generation methodology of the networks that presented the best results was also applied to independent data to evaluate its capability to estimate volumes. To do so, the data were randomly divided in three groups, where: 60% of the data were designated to training (934 trees), 20% (311) were used to testing and 20% (311 trees) were used in generating.

RESULTS AND DISCUSSION

Table 1 presents the data description showing the amplitude of values for each variable. A wide variation can be noticed, with *DBH* values ranging from 6.05cm up to 32.47cm, the same can be noticed for the total height, in which the variation was from 8.78m up to 43.80m.

Table 1: Descriptive statistics of the values used to build the artificial neural networks.

Variables	Values		
	Minimum	Medium	Maximum
DBH	6.05	15.87	32.47
D 0.0	6.68	18.89	40.11
D 0.5	6.05	16.96	37.56
D 1.0	5.89	16.14	32.95
D 1.5	5.41	15.60	31.99
D 2.0	5.25	15.19	31.67
Ht	8.78	25.24	43.80
V2	0.005630	0.047439	0.178718
S	1.08	1.65	2.32
Total Vol.	0.013232	0.295333	1.591495

in which: *DBH* is the diameter at the height of 1.30 m in cm, *Di* mean diameter position *i*, with *i* varying from 0.0, 0.5, 1.0, 1.5 and 2.0, in cm; *Ht* is the total height in m; *V2* is the volume up to 2 m of total height of tree, in m³; *S* is the slenderness degree, and *Total Vol.* is the total volume of tree, in m³.

The calculus of the categorical variable that presents the stem form resulted in 57% of the trees being classified up to 2 meters tall as cylindrical (*CI*) and in 43% of the situations, classified as parabolic (*PA*). There was no record in the database of the trees with stem up to 2 meters tall classified as conic (*CO*) or "neiloide" (*NE*). This may be related to the fact that the trees stems present diverse forms, from conic, going through cylindrical, until parabolic (Husch *et al*., 2003), and that stem is dependent on the local conditions and growth rate.

Table 2 presents the description of five retained networks for each group of input variables and the respective training statistics. In figure 1 the graphics of percentage residues are shown (dispersion and histogram).

Through the results analysis it is possible to observe that the networks differed little between themselves, and that in general, the correlations observed in the generalization phase were at 0.9971 and 0.9982, and the root mean square error values ranged from 5.34 up to 6.34%.

The residues histogram and dispersion graphics (figure 1) show that in most of the situations, satisfactory estimations were obtained, with errors concentrated in the class of 0%, tending to normality.

When analyzing the dispersion and frequency graphics, we can perceive that the networks estimations tended to small trees (with lower observed volume), sometimes overestimating, sometimes underestimating. Showing a certain difficulty to estimate accurately volumes in these situations. This result may be because of the low volume observed in trees, causing the estimates diversions, even if small, to result in a high percent value in the residue calculation, affecting the graphics of dispersion and frequency histogram.

Analyzing the results found by Binoti *et al*., (2014), we can notice that, although the estimates of volumes have been statistically similar to the volumes observed, there is a higher difficulty for the ANN to estimate smaller trees volume.

It seems like the addition of the slenderness degree and categorical variables representing the form of the stem did not result in improvement in the estimates, since the results were similar to the ones obtained through the networks generated without those input variables, and sometimes lower in some situations, like network 4 from the group of input variables 3 that resulted in negative estimate of volume in a certain occasion. Other results also prove that observation, like the increase in the values of

bias and RMSE, and the decrease in the correlation values observed to the networks of the group of input variables 4. Possibly, slenderness degree variable is little efficient to represent the trees form, being more related to the trees stability, according to Durlo and Dernadi (1998). And for the variable representing the form of stem, this result can be explained by the inefficiency of the methodology to determine the form of the stem of the trees up to 2 meters tall.

Table 2: Characteristics of the five best artificial neural networks by set of input variables and statistical estimates of the total volume of trees.

Input	Input Variables	ANN	Architecture	Training index	Selection index	Generalization index	Generalization		
							bias (m^3)	*RMSE* (%)	$r_{\hat{v}v}$
1	*DBH*; *D*0.0; *D*0.5; *D*1.0; *D*1.5; *D*2.0; *Ht*	1	7 – 6 – 1	0.067	0.070	0.070	0.0007	6.17	0.9976
		2	7 – 1 – 1	0.067	0.070	0.070	-0.0002	6.13	0.9976
		3	7 – 5 – 1	0.067	0.069	0.069	-0.0004	6.11	0.9976
		4	7 – 1 – 1	0.068	0.069	0.070	-0.0001	6.17	0.9976
		5	7 – 2 – 1	0.067	0.069	0.070	0.0000	6.13	0.9976
2	*DBH*; *D*0.0; *D*0.5; *D*1.0; *D*1.5; *D*2.0; *Ht; V2*	1	8 – 1 – 1	0.072	0.075	0.066	-0.0005	5.89	0.9978
		2	8 – 2 – 1	0.072	0.073	0.065	-0.0003	5.83	0.9979
		3	8 – 2 – 1	0.074	0.073	0.067	-0.0004	5.97	0.9978
		4	8 – 3 – 1	0.069	0.072	0.063	-0.0003	5.61	0.9980
		5	8 – 2 – 1	0.070	0.071	0.063	0.0001	5.62	0.9980
3	*DBH*; *D*0.0; *D*0.5; *D*1.0; *D*1.5; *D*2.0; *Ht; V2; S;*	1	9 – 10 – 1	0.072	0.071	0.064	-0.0003	5.57	0.9980
		2	9 – 3 – 1	0.073	0.071	0.066	-0.0002	5.76	0.9979
		3	9 – 2 – 1	0.072	0.071	0.063	-0.0001	5.51	0.9980
		4	9 – 2 – 1	0.071	0.071	0.061	0.0001	5.34	0.9982
		5	9 – 1 – 1	0.072	0.070	0.064	-0.0004	5.62	0.9980
4	*DBH*; *D*0.0; *D*0.5; *D*1.0; *D*1.5; *D*2.0; *Ht; V2; S; F*	1	13 – 5 – 1	0.070	0.066	0.074	-0.0007	6.17	0.9973
		2	13 – 1 – 1	0.072	0.066	0.075	-0.0008	6.26	0.9972
		3	13 – 2 – 1	0.071	0.066	0.076	-0.0008	6.34	0.9971
		4	13 – 2 – 1	0.071	0.065	0.075	-0.0007	6.25	0.9972
		5	13 – 1 – 1	0.069	0.064	0.073	-0.0008	6.16	0.9973

in which: *DBH* is the diameter at the height of 1.30m in cm, *Di* mean diameter position *i*, with *i* varying from 0.0, 0.5, 1.0, 1.5 and 2.0, in cm; *Ht* is the total height in m; *V2* is the volume up to 2 m of total height of tree, in m^3; *S* is the slenderness degree; *F* is a categorical variable representing the stem form up to 2 m of height.

The results show that the group of input variables 2 (*DBH*, *D0.0*, *D1.0*, *D1.5*, *D2.0*, *Ht* and *V2*) has generated the networks that presented better development. For input 2 group, the ANN 5 was superior to the other ones, with high correlation value observed (0.9980) and low RMSE and bias values observed, being respectively 5.61 % and 0.0001 m^3, in the generalization phase. The residues dispersion graphic for this network has shown little tendency to overestimation for small trees and the histogram presented higher concentration of the data in the class of 0 % and distribution tending to normality (figure 1). That network and the best network generation methodology were applied to the independent data.

The description of the data used in the validation phase are presented in Table 3, and it shows the amplitude of the values for each variable. We can perceive a wide variation in the data, and the values of *DBH* range from 5.00 cm to 28.25 cm, and the total height varied from 6.70 m to 32.70 m.

The network 5 from input 2 variables group application had a correlation among the volumes observed and estimated at 0.9956, the RMSE value was 8.84 % and the bias value was 0.0045 m^3. In around 40 % of the observations the residues were rated as 0 %.

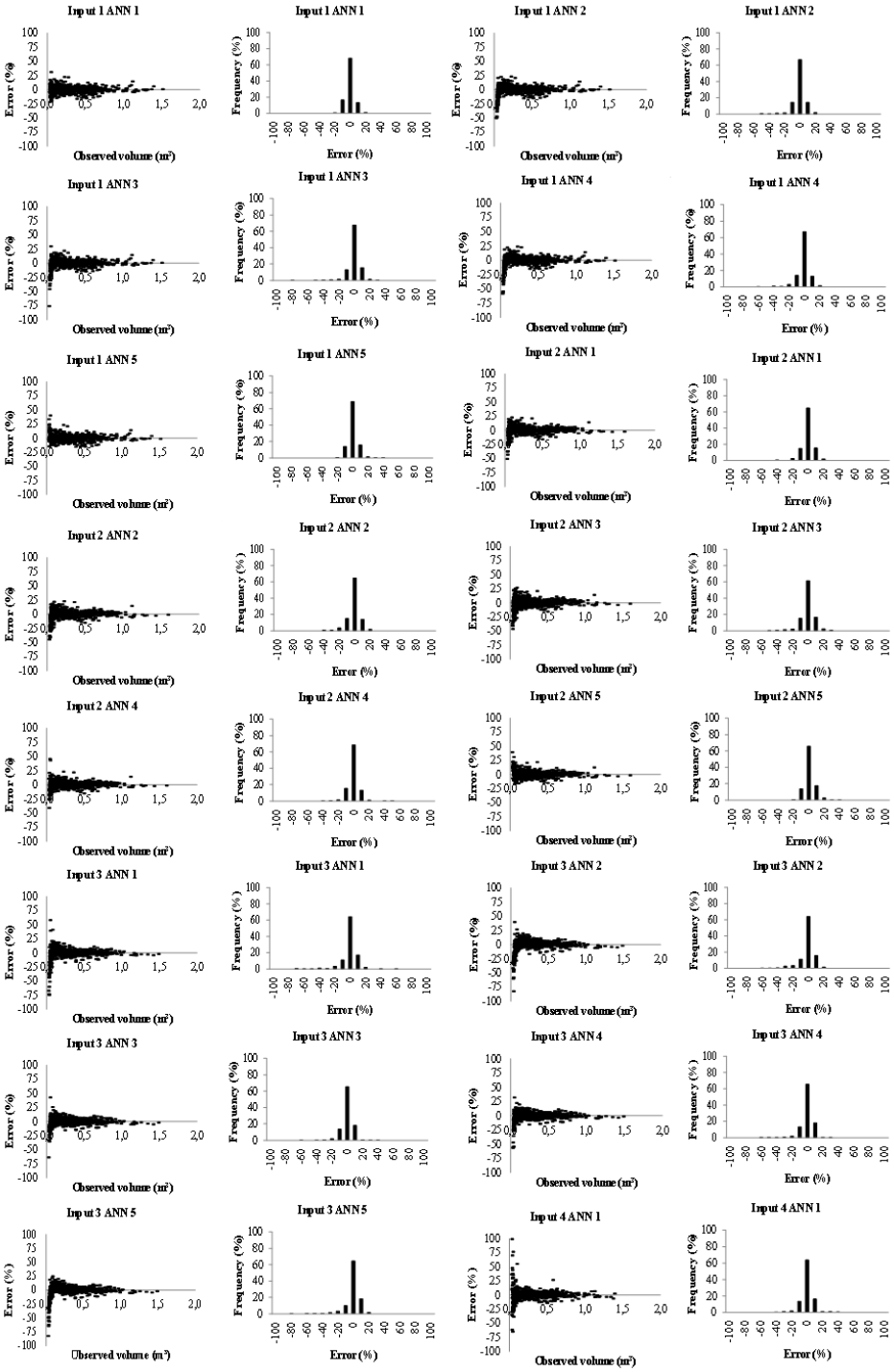
These numbers indicate a satisfactory result, but when analyzing the figure 2, where percentage residue graphics are presented (dispersion and histogram), it is possible to perceive that the estimates generated presented a strong tendency to small trees volume overestimation, evidencing a lower improvement when used to predict independent data volumes.

These results can be explained because of the fact that the data are a lot diverging from the ones used in the network creation procedure, like it occurs when we work with volume equations that are

adjusted taking to account the genetic material, age of trees, different spacing and environmental conditions, which are information that influence in the growth rate, form of stem and, consequently, the trees volume. This result makes clear the necessity to use artificial neural networks, such as volumetric equations, in conditions that are similar to the ones they were adjusted, and it may incur in tendentious estimates in case that condition is not respected.

Table 4 presents the description of the best 5 networks generated by the input group 2 in validation phase (*DBH*, *D*0.0, *D*0.5, *D*1.0, *D*1.5, *D*2.0, *Ht*, and *V2*), and the quality statistics of the estimates provided by them. In figure 4 percentage residues graphics are presented (dispersion and histogram).

By the results presented in table 4 we can notice that the neural networks generated provided satisfactory volume estimates. The bias values observed were lower than 0.0007 m³, the higher value noticed for the root mean square error (RMSE) was 7.59% and the correlation values were higher than 0.9955.



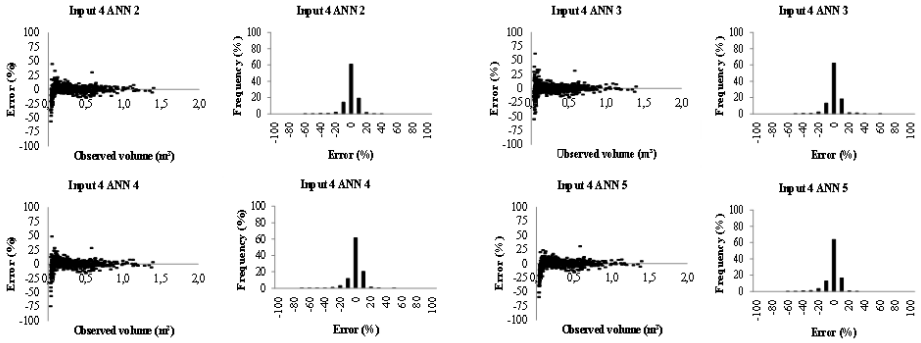


Fig. 1: Percent residual dispersion according to the volumes observed and percentage frequency of the percentage residues of the five best ANN each set of input variables with the data from the generalization phase.

Table 3: Descriptive statistics of values used in validation phase.

Variables	Values		
	Minimum	Medium	Maximum
DBH	5.00	13.98	28.25
D 0.0	5.40	16.95	38.00
D 0.5	5.30	15.24	32.50
D 1.0	5.20	14.33	30.00
D 1.5	5.00	13.90	28.50
D 2.0	4.40	13.18	27.00
Ht	6.70	18.07	32.70
V2	0.004211	0.038313	0.146817
Total Vol.	0.006984	0.155157	0.761916

in which: *DBH* is the diameter at the height of 1.30 m from soil, in cm; *Di* means diameter position *i*, with *i* varying from 0.0, 0.5, 1.0, 1.5 and 2.0, in cm; *Ht* is the total height in m; *V2* is the volume up to 2 m of height of tree, in m³; and *Total Vol.* is the total volume of tree, in m³.

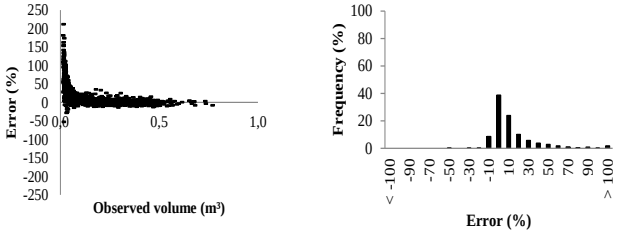


Fig. 2: Percentage residual dispersion according to the observed volume and frequency percentage of residues for estimated volume with the best ANN data designed for validation.

Table 4: Characteristics of the five best artificial neural networks for the set of input variables 2 and statistics of the estimates of the total volume of trees in the generalization phase with the data validation.

Input	Input Variables	ANN	Architecture	Training index	Selection index	Generalization index	Generalization		
							bias (m³)	*RMSE* (%)	$r_{\hat{v}v}$
2	*DBH*; *D*0.0; *D*0.5; *D*1.0; *D*1.5; *D*2.0; *Ht; V2*	1	8 – 1 – 1	0.091	0.084	0.095	0.0007	7.59	0.9955
		2	8 – 2 – 1	0.084	0.080	0.090	0.0006	7.16	0.9960
		3	8 – 4 – 1	0.083	0.080	0.086	0.0007	6.83	0.9963
		4	8 – 3 – 1	0.083	0.080	0.087	0.0005	6.91	0.9963
		5	8 – 5 – 1	0.082	0.080	0.088	0.0005	7.00	0.9962

where: *DBH* is the diameter at the height of 1.30 m in cm; *Di* means diameter position *i*, with *i* varying at 0.0, 0.5, 1.0, 1.5 and 2.0, in cm; *Ht* is the total height in m; *V2* is the volume up to 2 m of total height of tree, in m³.

In figure 4 it is evidenced that the networks that presented good estimates, since the dispersion and residues histogram graphics presented, mostly, error concentrated in the class of 0%, tending to normality.

These results show the efficiency of the artificial neural networks as a tool to estimate the trees total volume based on measurements up to 2 meters tall, agreeing with the results obtained in the works of Gorgens *et al*., (2009), Silva *et al*., (2009), Binoti (2012) and too Binoti *et al*., (2014) that estimated the trees volume with the artificial neural networks based on several diameters along the whole tree.

The network 1 presented tendency to overestimation of volume for smaller trees, while the network 3 showed more tendency to underestimate the volume for small trees. The other networks 2, 4

and 5 did not present tendencies; however it is possible to notice a higher dispersion of the residues in the lowest volumes observed, indicating that to smaller trees have a loss of estimates quality, however this problem did not affect the estimates, because the root mean square error (RMSE) were satisfactory.

To an admitted error of up to 10% in the volume estimated value, we can conclude that the neural networks generated with the input variables *DBH*, *D0.0*, *D0.5*, *D1.0*, *D1.5*, *D2.0*, *Ht* and *V2* provided satisfactory volume estimates and we must point out to the ease to collect this information in field, since the diameters up to 2 meters tall can be easily and safely measured, and there isn't the need to collect diameters in higher heights.

The results obtained in this work show the risk in using a neural network in conditions that are different from the ones from which they were generated, characteristics considered most expressive by the network in a certain condition, can be less relevant in other occasions, resulting in tendentious volume estimates and, consequently, compromising the whole company planning.

It is convenient to point out that this methodology developed in this work does not replace the traditional methods to determine the trees volume, but it is and alternate tool the occasions where the traditional methods would be impossible to be applied, for example, when there is restriction to the cut of trees and in case of experimental tests.

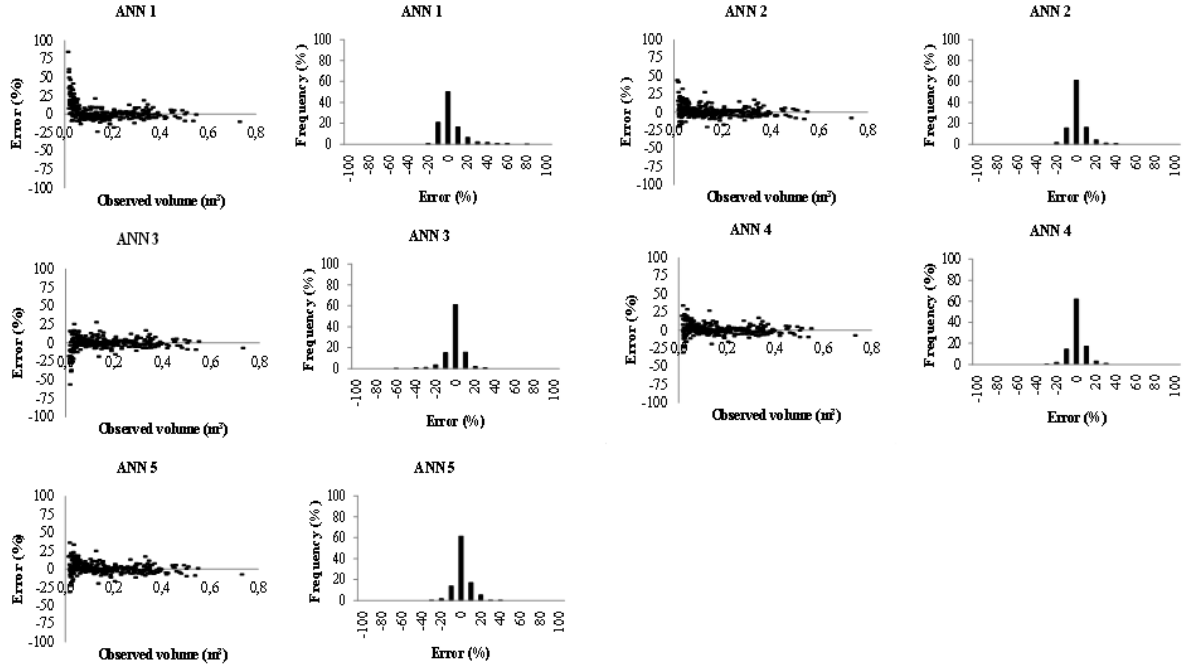


Fig. 3: percentage residues dispersion and frequency percentage of percentage residues for the best 5 ANN generated through the input variables 2, in the generalization phase for the validation data.

Conclusions:

It is possible to precisely estimate the trees volume basing on variables collected under 2 the height meter of the tree the total height using artificial neural networks;

The set of input variables in the networks that provided the best volume estimates were *DBH*, the average diameters ant 0.0, 0.5, 1.0, 1.5, 2.0, total height and stem volume up to 2 meters of height;

The artificial neural networks did not provide precise volume estimates when applied to independent data from which they were trained.

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