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STEM TAPERING OF *Eucalyptus* spp. USING DIFFERENT CONFIGURATIONS OF ARTIFICIAL NEURAL NETWORKS

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Resumo

Afilamento do fuste de Eucalyptus spp. utilizando diferentes configurações de redes neurais artificiais. O objetivo desse trabalho foi testar e avaliar diferentes configurações de redes neurais artificiais (RNAs) para a modelagem do afilamento do fuste de árvores em povoamentos de *Eucalyptus* spp. na microrregião de Pirapora, Minas Gerais. Os dados utilizados foram provenientes de 8.410 árvores de *Eucalyptus* spp. em diferentes idades de rotação. As variáveis quantitativas mensuradas foram: idade, altura total, diâmetro a 1,30 m de altura (dap), diâmetro e altura em diferentes posições no fuste. A única variável qualitativa mensurada foi o clone. Quatro cenários foram avaliados: cenário 1 com as entradas Ht, dap, h_i, I e Clone; cenário 2 com Ht, dap, h_i e Clone; cenário 3 com Ht, dap, h_i e I; e cenário 4 com Ht, dap e h_i. Diferentes topologias de RNAs do tipo *Multilayer Perceptron* foram testadas. As RNAs 102 (neurônios na camada oculta=18; função = Exponencial; algoritmo = Rprop), 91 (neurônios na camada oculta = 19; função = Exponencial; algoritmo = Rprop), 13 (neurônios na camada oculta = 7; Função = Exponencial; Algoritmo = SCG) e 27 (neurônios na camada oculta = 6; função = Exponencial; algoritmo = Rprop) apresentaram as melhores medidas de precisão estatísticas no treinamento para predizer o afilamento nos cenários 1, 2, 3 e 4, respectivamente. A RNA 103 (neurônios na camada oculta = 19; função = Exponencial; algoritmo = Rprop) do cenário 1 apresentou bons resultados estatísticos na validação. Desse modo, as RNAs foram eficientes para predizer o diâmetro ao longo do fuste das árvores de *Eucalyptus* spp.

Palavras-chave: Modelagem do afilamento; *Multilayer Perceptron*; Topologias de redes.

Abstract

The objective of this work was to test and evaluate different configurations of artificial neural networks (ANNs) for modeling tree stem taper in *Eucalyptus* spp. in strands in the microregion of Pirapora, Minas Gerais. The data used came from 8,410 *Eucalyptus* spp. at different speeds. The quantitative variables measured were: age, total height, diameter at the height of 1.30 m (dbh), diameter and height in different positions on the stem. The only qualitative variable measured was the clone. Four scenarios were evaluated: scenario 1 with Ht, dbh, h_i, A and Clone inputs; scenario 2 with Ht, dbh, h_i and Clone; scenario 3 with Ht, dbh, h_i and A; and scenario 4 with Ht, dbh and h_i. We tested different ANNs topologies of the Multilayer Perceptron type. The ANNs 102 (neurons in the hidden layer = 18; function = Exponential; algorithm = Rprop), 91 (neurons in the hidden layer = 19; function = Exponential; algorithm = Rprop), 13 (neurons in the hidden layer = 7; Function = Exponential; Algorithm = SCG) and 27 (neurons in the hidden layer = 6; function = Exponential; algorithm = Rprop) presented the best measures of statistical accuracy in training to predict the bottleneck in scenarios 1, 2, 3 and 4, respectively. The ANN 103 (neurons in the hidden layer = 19; function = Exponential; algorithm = Rprop) from scenario 1 presented good statistical results in the validation. Thus, the ANNs were efficient in predicting the diameter along the *Eucalyptus* spp stem.

Keywords: Taper modeling; Multilayer Perceptron; Network topologies.

INTRODUCTION

Effectively estimating the tapering of the tree stem is essential for the conversion of wood into multiproducts to be conducted optimally. This is reflected in better use of raw materials and a significant increase in revenue from a forest stand (MARTINS *et al.*, 2016; CAMPOS *et al.*, 2017). The term taper represents the taper of the trunk of a tree and its models result in diameter information at any height of the tree as long as it presents a regularity in its change (MARTINS *et al.*, 2016).

Diameters are obtained by rigorous cubing, which in addition to being a procedure with high operational cost, causes significant tree losses, mainly due to the need to periodically perform the procedure to adjust more accurate models (CURTO *et al.*, 2019). Therefore, adopting more viable modeling techniques is important to generate more accurate predictions, such as artificial intelligence techniques. These techniques have been used in the forestry sector mainly through artificial neural networks (ANNs), with emphasis on dendrometric predictions (CERQUEIRA *et al*, 2018; REIS *et al.*, 2018). ANNs have characteristics that make them efficient for modeling dendrometric variables, such as the ability to generalize, capture linear and non-linear relationships between variables, noise tolerance, allows the addition of qualitative variables, among others (MARTINS *et al.*, 2016; CAMPOS *et al.*, 2017; BONETE *et al.*, 2020). In addition, studies that evaluate the best configuration of ANNs for predicting the diameter along the stem are rare.

ANNs compose a set of nonparametric techniques formed by simple mathematical processing units called neurons, which constitute a parallel distributed system (HAYKIN, 2001; SCHIKOWSK *et al.*, 2015). Through the learning process of ANNs, it is possible to generalize your acquired knowledge and apply it to another unknown database that has similar characteristics and variables, and also extract non-explicit characteristics from the data set provided (HAYKIN, 2001; LEITE *et al.*, 2011).

Mendonça *et al.* (2015) when applying ANNs to predict the diameter (d_i) along the stem (h_i) in *Eucalyptus* spp. found efficient results and considered the technique as a good alternative for use and application. However, choosing the appropriate ANN configuration and input variables is a process that can take a long time, due to the many possibilities of combinations, and is usually chosen empirically based on user experience or through trial and error (BINOTI *et al.*, 2014).

Therefore, the objective of this work was to test and evaluate different configurations of artificial neural networks for modeling the trees' stem taper of forest stands of *Eucalyptus* spp. in the Pirapora microregion, Minas Gerais.

MATERIAL AND METHODS

Characterization of the study area

We conducted the study on five farms in the microregion of Pirapora (northern mesoregion of Minas Gerais), in stands of *Eucalyptus* spp. at different rotation ages driven by the high forest system (1st rotation). The microregion of Pirapora is composed of 10 municipalities: Buritizeiro, Ibiaí, Jequitaí, Lagoa dos Patos, Lassance, Pirapora, Riachinho, Santa Fé de Minas, São Romão and Várzea da Palma. With a population of approximately 165,683 inhabitants and an area of 23,068 km² (IBGE, 2011).

According to the Köppen-Geiger classification, the climate is Aw, humid tropical, characterized by two well-defined seasons. The dry season runs from autumn to winter, and the wet season runs from spring to summer. The average annual precipitation ranges from 1,000 to 1,200 mm and average temperatures from 22ºC to 24ºC (ALVARES *et al.*, 2013).

Data collection

We obtained the data used from 8,410 commercial *Eucalyptus* spp. clone trees, namely: GG100, I144, I224, 42, 3487 and 6382 with 1,047, 2,283, 2,326, 552, 1799 and 433 trees, respectively. The six clones are hybrids of *Eucalyptus urophylla* vs *Eucalyptus grandis*. We distributed the clones in 18 plots with areas ranging from 12.35 to 51.45 hectares, with a mean of 32.45 hectares. The quantitative variables measured were: age, total height, diameter at 1.30 m high (dbh), height in different positions on the stem and diameter in different positions (Table 1). The only qualitative variable measured was the clone.

Table 1. Descriptive statistics for the study area.
Tabela 1. Estatísticas descritivas para a área de estudo

Variables	Minimum	Maximum	Mean	Mean's Standard Deviation
A (years)	7,1	10,9	8,6	1,21
Ht (m)	9,8	31,1	22,9	4,19
dbh (cm)	6,5	24,0	14,7	3,84
h_i (m)	0,0	29,2	6,7	6,79
d_i (cm)	3,0	41,4	12,4	4,90

Subtitle: A, age; Ht, total height; dbh, diameter at 1.3 m height; h_i, height at different positions on the stem; d_i, diameter at different positions on the stem

Data preprocessing

We conducted data preprocessing through linear normalization of the quantitative variables (Equation 1), in order to rescale the amplitude and magnitude of the variables for the interval from 0 to 1. Thus, we obtained the predictions according to the domain of the activation functions of neurons in the intermediate and output layers.

In addition, normalization can prevent networks from assigning greater importance to larger scale variables. The qualitative variable was divided into 6 classes and coded in binary numbers.

$$v' = \frac{v - \min(v)}{\max(v) - \min(v)}(max_{new} - min_{new}) + min_{new} \quad (1)$$

where: $\min(v)$: smallest value from the training database, $\max(v)$: largest value from the training database, max_{new}: largest normalization value and min_{new}: lowest normalization value.

ANNs training

We randomly divided manually the data set into two groups, with approximately 50% of the total data for each group. Group 1 was used for training the ANNs, consisting of 4,199 trees. Group 2 was used to validate the ANNs, consisting of 4,211 trees. The proportion of training data was enough to represent the heterogeneity of the database, not requiring a higher percentage of data for training. In addition, increasing the percentage of data for training would increase the computational cost.

We tested different network topologies of the Multilayer Perceptron (MLP) type. The intervals of the number of neurons in the only hidden layer of the networks were defined by the Fletcher-Gloss method: $2 \times \sqrt{n} + n_2 \leq n_1 \leq 2 \times n + 1$ (SILVA *et al.*, 2010). Where: n = number of network inputs, n_1 = amount of neurons in the hidden layer and n_2 = amount of neurons in the output layer. Table 2 shows the interval of the number of neurons in the hidden layer for each scenario of variables tested during training.

Table 2. Characteristics of each evaluated scenario.
Tabela 2. Características de cada cenário avaliada.

Scenario	Input variables	Intervalo de números de neurônios[1]	Output variable
1	Ht, dbh, h_i, A, Clone	7 to 21	d_i
2	Ht, dbh, h_i, Clone	7 to 19	d_i
3	Ht, dbh, h_i, A	5 to 9	d_i
4	Ht, dbh, h_i	4 to 7	d_i

Subtitle: dbh, diameter at 1.3 m height; Ht, total height; h_i, height at different positions on the stem; A, age; d_i, diameter at different positions in the stem; [1]Interval of numbers of neurons tested in the hidden layer.

The tested activation functions, in all scenarios in the middle layer, were the exponential, identity, logistic and hyperbolic tangent. In the output layer, we always used the linear function was to predict the relative diameter along the stem. The training algorithms used in these scenarios were the Resilient Propagation (Rprop) and the Scaled Conjugate Gradient (SCG). The initial weights of the ANNs were randomly generated. The learning rate was equal to 0.2. The training stopping criterion was 3000 cycles. For each scenario, 120 networks were trained, totaling 480 networks. We conducted the construction, training and validation of the ANNs in the R software, version 3.5.2, with the "RSNNS" package. (BERGMEIR; BENITEZ, 2012).

Evaluation of ANNs

We used the following criteria to evaluate the ANNs:

a) Graphic analysis of residuals:

With the percentage errors calculated by Equation 2:

$$Error\ (\%) = \frac{Y - \hat{Y}}{Y} * 100 \quad (2)$$

where: Y: observed diameter e $\hat{Y}$: predicted diameter.

b) Root mean squared error in percentage - RMSE% (Equation 3)

$$RMSE(\%) = \frac{100}{\bar{Y}}\sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n}} \quad (3)$$

where: $\bar{Y}$: mean diameter; Y: observed diameter, $\hat{Y}$: predicted diameter and n: number of observations.

c) Determination coefficient (R^2):

We used Equation 4 to calculate the determination coefficient between the observed and predicted values

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \quad (4)$$

where: R^2: determination coefficient, Y: observed diameter, $\hat{Y}$: predicted diameter, $\bar{Y}$: arithmetic mean of observed diameters and n: number of observations.

e) Mean absolute error – MAE (Equation 5):

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} \left|\hat{Y}_i - Y_i\right| \quad (5)$$

where: Y: observed diameter, $\hat{Y}$: predicted diameter and n: number of observations.

The three most accurate ANNs in the training of each evaluated scenario were chosen from the lowest RMSE (%), highest R^2, lowest MAE and best graphic behavior of the residuals.

Validation

After training, the ANNs were applied to the group 2 dataset for validation, in order to evaluate the accuracy of the ANNs generated during training. We used the same training statistics to evaluate the accuracy of the predictions.

RESULTS

In the selection of the best configurations in training, networks 102, 91, 13 and 27 presented the best tapering accuracy measures in scenarios 1, 2, 3 and 4, respectively (Table 3). We observed that the best ANNs had in common the exponential-type activation function and the Rprop-type training algorithm.

Table 3. Training quality statistics for the three best artificial neural networks selected in each scenario to predict the relative diameter of *Eucalyptus* spp. trees in the microregion of Pirapora-MG.

Tabela 3. Estatísticas de qualidade do treinamento das três melhores redes neurais artificiais selecionadas em cada cenário para predizer o diâmetro relativo de arvores de *Eucalyptus* spp. na microrregião de Pirapora-MG.

Scenario	Network	Number of neurons	Activation function	Algorithm	R^2	RMSE (%)	MAE
1	102	18	Exponential	Rprop	0.9526	8.5	0.65
1	103	19	Exponential	Rprop	0.9512	8.7	0.65
1	101	17	Exponential	Rprop	0.9498	8.8	0.66
2	91	19	Exponential	Rprop	0.9506	8.7	0.62
2	85	13	Exponential	Rprop	0.9469	9.0	0.66
2	89	17	Exponential	Rprop	0.9463	9.1	0.66
3	13	7	Exponential	SCG	0.9322	10.2	0.74
3	32	6	Exponential	Rprop	0.9316	10.3	0.74
3	24	8	Logistics	Rprop	0.9312	10.3	0.80
4	27	6	Exponential	Rprop	0.9314	10.3	0.79
4	20	7	Logistics	Rprop	0.9310	10.3	0.80
4	14	5	Hyperbolic Tangent	SCG	0.9310	10.3	0.74

Subtitle: R^2, determination coefficient; RMSE, Root mean squared error in percentage; MAE, mean absolute error.

Based on the validation quality statistics (Table 4), the quality and the best results were confirmed for the predictions of the training ANNs, selecting ANNs 91 and 103, which have the same number of neurons in their topology (19), using the Rprop algorithm and with an exponential activation function. The difference between these ANNs is the presence of the age variable in scenario 1. Scenario 1 presented a better statistical result in the generated ANNs when compared to the other scenarios, with emphasis on ANN 103 that presented $R^2 = 0.9606$ and RMSE = 10.3%.

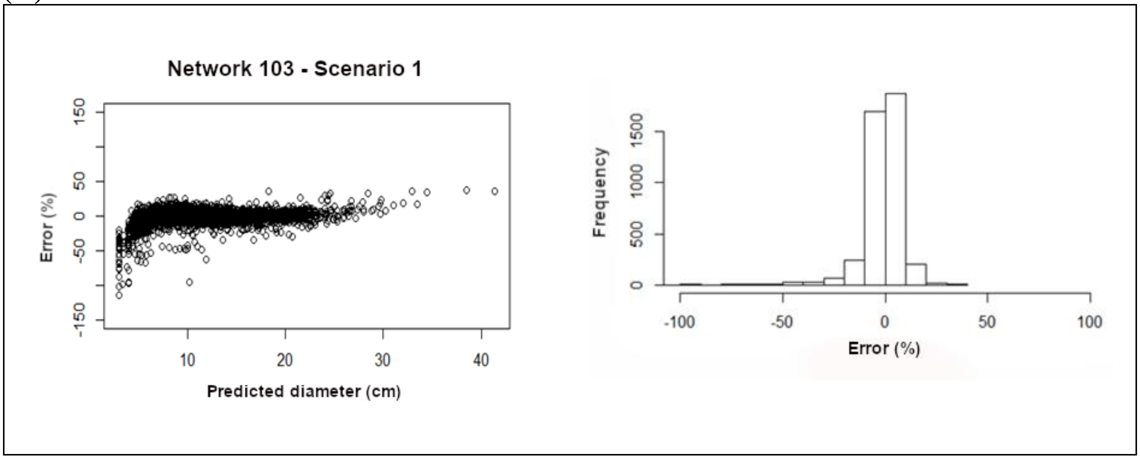
The ANNs of scenarios 3 and 4, which have the number of neurons varying between 9 and 4, presented the worst training and validation results (Table 3 and 4).

Table 4. Validation quality statistics of the three best artificial neural networks selected in each scenario to predict the relative diameter of *Eucalyptus* spp. trees in the microregion of Pirapora-MG.
Tabela 4. Estatísticas de qualidade da validação das três melhores redes neurais artificiais selecionadas em cada cenário para predizer o diâmetro relativo de arvores de *Eucalyptus* spp. na microrregião de Pirapora-MG.

Scenario	Network	Number of neurons	Activation function	Algorithm	R^2	RMSE (%)	MAE
1	102	18	Exponential	Rprop	0.9584	10.4	0.97
1	103	19	Exponential	Rprop	0.9606	10.3	0.95
1	101	17	Exponential	Rprop	0.9592	10.4	0.98
2	91	19	Exponential	Rprop	0.9612	10.2	0.94
2	85	13	Exponential	Rprop	0.9577	10.4	0.94
2	89	17	Exponential	Rprop	0.9571	10.6	0.98
3	13	7	Exponential	SCG	0.9450	11.3	0.92
3	32	6	Exponential	Rprop	0.9485	11.2	1.02
3	24	8	Logistics	Rprop	0.9461	11.2	1.02
4	27	6	Exponential	Rprop	0.9467	11.6	1.09
4	20	7	Logistics	Rprop	0.9461	11.1	1.02
4	14	5	Hyperbolic Tangent	SCG	0.9423	12.2	1.04

Subtitle: R^2, determination coefficient; RMSE, Root mean squared error in percentage; MAE, mean absolute error.

Among the 12 best selected ANNs, 10 presented the Rprop algorithm. In validation, networks 103, 91, 32 and 20 presented the best tapering accuracy measures in scenarios 1, 2, 3 and 4, respectively. ANNs 103 from scenario 1 and 91 from scenario 2 were selected for the presentation of training residuals graphs (Figure 1) and validation (Figure 2) because these networks are the best in validation, with higher R^2 values and lower RMSE (%) and MAE.



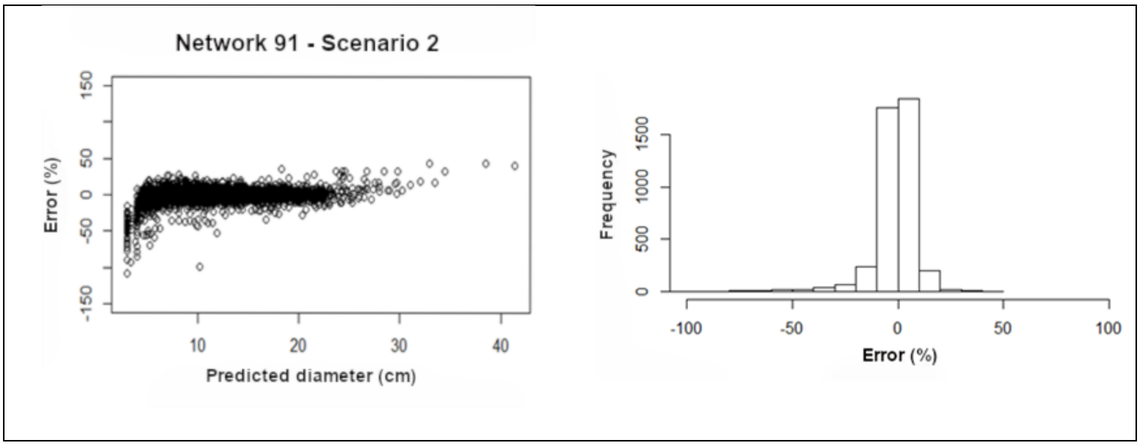


Figure 1. Graphical analysis of the training of the best networks.
Figura 1. Análise gráfica do treinamento das melhores redes.

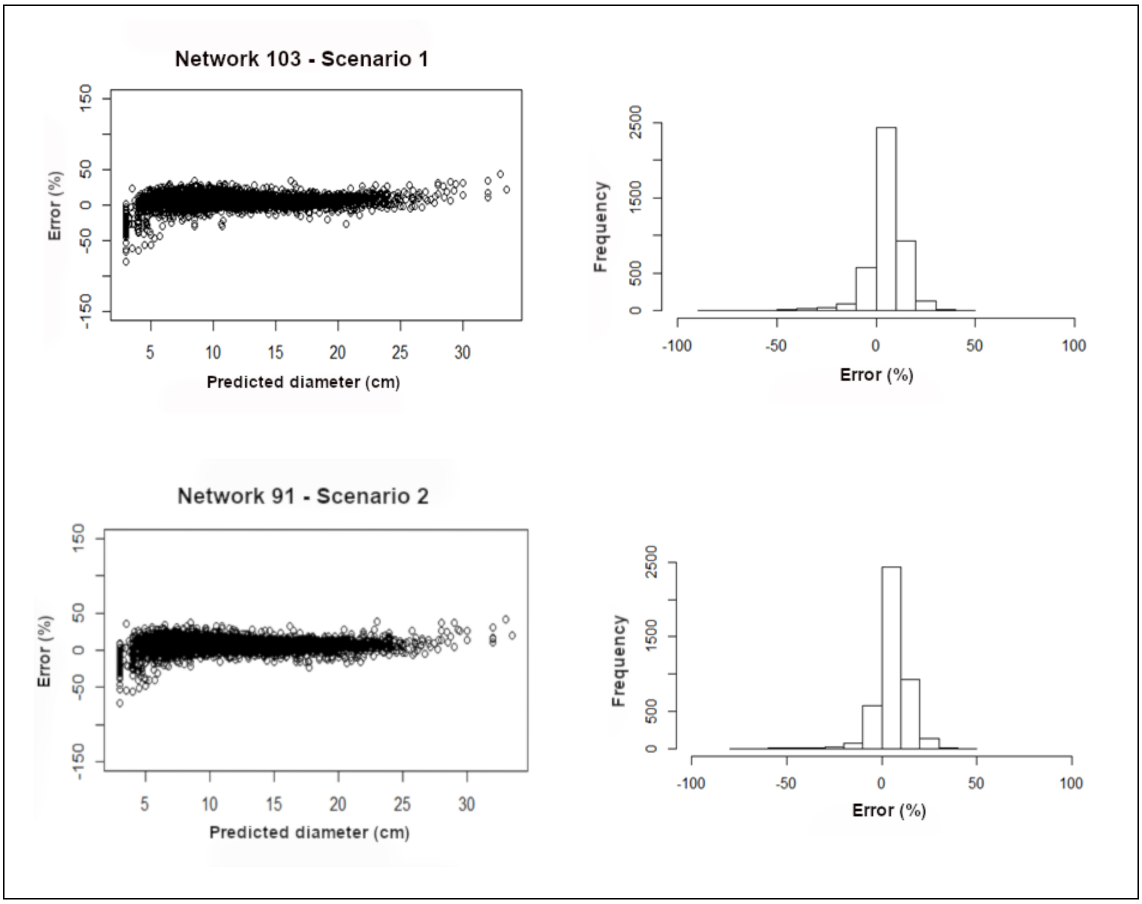


Figure 2. Graphical analysis of the validation of the best networks.
Figura 2. Análise gráfica da validação das melhores redes.

When conducting the graphical analysis of residuals, for the training of scenarios 1 and 2, we observed a greater dispersion of the error for diameters smaller than 10 cm. When evaluating the histogram of residues (Figures 1 and 2), the distribution was symmetrical with mean close to zero.

The quality of the ANNs in scenario 1 was confirmed through validation, with an increase in the R^2 between the observed and predicted values and a reduction in the RMSE%. Thus, ANN 103 from scenario 1 was selected as the best network in this study.

DISCUSSION

The ANN technique has been widely used in studies of tapering, emerging as a viable alternative, accurate and with less dispersion of errors, compared to traditional modeling methods (MARTINS *et al.*, 2017; BONETE *et al.*, 2020). In the present study, the evaluated and selected nets are applicable and recommended for the study of stem tapering for species of *Eucalyptus* spp. in the Pirapora microregion, Minas Gerais.

The presence of the exponential activation function in the best training ANNs indicates that the relationship between the independent variables and the dependent variable has a non-linear relationship. This reinforces the ability of ANNs to model non-linear problems, such as the prediction of the diameter along the stem of *Eucalyptus* spp. (CAMPOS *et al.*, 2017; CUNHA NETO *et al.*, 2019). The better performance of the Rprop algorithm may be associated with greater simplicity in its configuration, not being necessary to define, for example, the learning rate (MARTINS *et al.*, 2016; CAMPOS *et al.*, 2017). Martins *et al.* (2016) also observed good performance of the Rprop algorithm when evaluating different network configurations for estimating eucalyptus stem tapering, proving the ability of this algorithm to model tree diameters.

The highest values of R^2 and the lowest values of RMSE and MAE for the configurations that present the independent variable age suggest that the behavior of the shape of the trees in each phase of their growth was captured. In this way, the greatest accuracy is guaranteed, allowing the model to describe the variation in the diameter of the stem at each age (FIGUEIREDO FILHO *et al.*, 2015; MARTINS *et al.*, 2016). Considering the results of the different scenarios evaluated in this research, the age variable positively influences the modeling, indicating the insertion of this variable in the ANN models used to predict the diameter along the stem. Soares *et al.* (2012) found RMSE values between 2 and 21% and R^2 above 0.90 for predicting the diameters of eucalyptus trees using MLP networks, corroborating the results presented in the present study.

By evaluating the input variables in scenarios 1, 2, 3 and 4, when reducing the number of ANN variables, there was a reduction in R^2 and an increase in RMSE, reducing the reliability of the adjusted models. However, this tendency is not always observed, as observed by Schikowski *et al.* (2015) who, when evaluating the prediction of the stem shape using the ANNs, did not show improvement in the predictions, even evaluating networks with different numbers of variables in the input layer.

The greater dispersion of the error observed in the prediction of tree apex values, in diameters smaller than 10 cm, were also found in some works involving ANN models (MÜLLER *et al.*, 2014; SCHIKOWSKI *et al.*, 2015; MENDONÇA *et al.*, 2015). When evaluating the histogram of residues, the symmetrical distribution with mean close to zero was similar to that found by Silva *et al.* (2016), confirming the accuracy of the ANNs technique applied in this work.

In general, advances with the use of ANNs led to the appearance of different available configurations that can be used in the modeling of forest variables (COSTA FILHO *et al.*, 2019). However, choosing the appropriate configuration and input variables in an ANN is a process that can take a long time (ROCHA *et al.*, 2021). The evaluation of different ANN configurations for modeling the stem tapering of trees is extremely important for the forestry sector, as it indicates the best ANN configurations for this application, among the many possible combinations. In addition, with just a few modifications in the ANN configuration, it was possible to observe an increase in the accuracy of the predictions. Therefore, the present study can be used as a guide for modeling the tapering of the *Eucalyptus* spp. with ANNs in order to obtain more accurate results, assisting in the decision making of forest managers.

CONCLUSIONS

- Artificial neural networks (ANNs) were efficient to predict the diameter along the stem of *Eucalyptus* spp. trees.
- ANN 103 from scenario 1, presented the best statistical results in the validation, with 19 neurons in the hidden layer, exponential activation function, Rprop algorithm, and the input variables total height (Ht), diameter at 1.30 m from the ground (dbh), height at different positions on the stem (h_i), age (A) and clones.
- Future studies should be conducted in order to test different packages and topologies of ANNs to obtain an ideal model in order to reach more accurate results for the prediction of tree diameters.
- Thus, considering the evaluation of scenarios by different age groups is recommended, in order to seek to increase the accuracy of the results.

REFERENCES

ALVARES, C. A.; STAPE, J. L.; SENTELHAS, P. C.; DE MORAES GONÇALVES, J. L.; SPAROVEK, G. Köppe's climate classification map for Brazil. **Meteorologische Zeitschrift**, v. 22, n. 6, p. 711–728, 2013.

BERGMEIR, C.; BENITEZ, J. M. Neural networks in R using the Stuttgart Neural Network Simulator: RSNNS. **Journal of Statistical Software**, Innsbruck, Áustria, v. 46, n. 7, p. 1–26, 2012.

BINOTI, D. H. B.; BINOTI, M. L. M. S.; LEITE, H. G. Configuração de redes neurais artificiais para estimação do volume de árvores. **Ciência da Madeira**, Pelotas, v. 05, n. 01, p. 58–67, 2014.

BONETE, I. P.; ARCE, J. E.; FIGUEIREDO FILHO, A.; RETSLAFF, F. A. S.; LANSSANOVA, L. R. Artificial neural networks and mixed-effects modeling to describe the stem profile of *Pinus taeda* L. **Floresta**, Curitiba**,** v. 50, n. 1, p. 1123–1132, 2020.

BRAGA, A. P.; CARVALHO, A. P. L.; LUDERMIR, T. B. Redes Neurais Artificiais: Teoria e Aplicações. **Editora LTC**, Rio de Janeiro, Brasil, 2000.

CAMPOS, B. P. F.; SILVA, G. F.; BINOTI, D. H. B.; MENDONÇA, A. R.; LEITE, H. G. Descrição do perfil do tronco de árvores em plantios de diferentes espécies por meio de redes neurais artificiais. **Pesquisa Florestal Brasileira**, Colombo, v. 37, n. 90, p. 99–107, 2017.

CERQUEIRA, C. L.; MÔRA, R.; TONINI, H.; ARCE, J. E.; CARVALHO, S. P. C.; CIARNOSCHI, L. D. Funções de afilamento para eucalipto em sistema de integração Lavoura Pecuária-Floresta. **Advances in Forestry Science**, Cuiabá, v. 5, n. 4, p. 479–485, 2018.

COSTA FILHO, S. V. S. da; ARCE, J. E.; MONTAÑO, R. N. R.; PELISSARI, A. L. Configuração de algoritmos de aprendizado de máquina na modelagem florestal: um estudo de caso na modelagem da relação hipsométrica. **Ciência Florestal**, Santa Maria, v. 29, n. 4, p. 1501-1515, 2019.

CUNHA NETO, E. M. C.; BEZERRA, J. C. F.; VERAS, H. F. P.; GOUVEIA, D. M.; ARAUJO, E. C. G.; SILVA, T. C. Estimativa do afilamento do fuste de indivíduos de eucalipto por meio de técnicas de inteligência artificial. **Biofix Scientific Journal**, Curitiba, v. 4, n. 2, p. 166–171, 2019.

CURTO, R. A.; LAURO, A. C.; TONINI, H.; KOHLER, S. V.; ARAÚJO, E. J. G.; BIAZATTI, S. C. Cubagem de árvores em pé com dendrômetro óptico em sistema de integração lavoura-pecuária-floresta. **Pesquisa Florestal Brasileira**, Colombo, v. 39, p. 1–11, 2019.

CZAJKOWSKI, M.; KRETOWSKI, M. Decision tree underfitting in mining of gene expression data. An evolutionary multi-test tree approach. **Expert Systems with applications**, v. 137, n. 15, p. 392–404, 2019.

FIGUEIREDO FILHO, A.; RETSLAFF, F. A. D. S.; KOHLER, S. V.; BECKER, M.; BRANDES, D. Efeito da idade no afilamento e sortimento em povoamentos de *Araucaria angustifolia*. **Floresta e Ambiente**, Seropédica, v. 22, n. 1, p. 50–59, 2015.

HAYKIN, S. **Redes neurais**: princípios e prática. 2. ed. Porto Alegre: Bookman, 2001. 900 p.

IBGE. INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA. Divisão regional do Brasil em Mesorregiões e Microrregiões geográficas. Rio de Janeiro: IBGE, v. 1. 2011.

LEITE, H. G.; SILVA, M. L. M.; BINOTI, D. H. B.; FARDIN, L.; TAKIZAWA, F. H. Estimation of inside-bark diameter and heartwood diameter for *Tectona grandis* Linn. trees using artificial neural networks. **European Journal of Forest Research**, Heidelberg, Germany, v. 130, n. 2, p. 263–269, 2011.

MARTINS, A. P. M.; DEBASTIANI, A. B.; PELISSARI, A. L.; MACHADO, S. D. A.; SANQUETTA, C. R. Estimativa do afilamento do fuste de araucária utilizando técnicas de inteligência artificial. **Floresta e Ambiente**, Seropédica**,** v. 24, 2017.

MARTINS, E. R.; BINOTI, M. L. M. S.; LEITE, H. G; BINOTI, D. H. B.; DUTRA, G. C. Configuração de redes neurais artificiais para estimação do afilamento do fuste de árvores de eucalipto. **Revista Brasileira de Ciências Agrárias**, Pernambuco, v. 11, n. 1, p. 33–38, 2016.

MENDONÇA, N. P.; CARVALHO, M. C.; GOMIDE, L. R.; FILHO, A. C. F.; FERREIRA, M. A. Previsão de diâmetros ao longo do fuste de eucalipto via redes neurais artificiais. **Enciclopédia Biosfera**, Goiânia, v. 11, n. 22, p. 2419–2429, 2015.

MÜLLER, M. D.; SALLES, T. T; PACIULLO, D. S. C.; BRIGHENTI, A. M.; CASTRO, C. R. T. Equações de altura, volume e afilamento para eucaplito e acácia estabelecidos em sistema silvipastoril. **Floresta**, Curitiba, v. 44, n. 3, p. 473–484, 2014.

REIS, P. C. M.; SOUZA, A. L.; REIS, L. P.; CARVALHO, A. M. M. L.; MAZZEI, L.; RÊGO, L. L. J. S.; LEITE, H. G. Artificial neural networks to estimate the physical-mechanical properties of amazon second cutting cycle wood. **Maderas. Ciencia y tecnologia**, v. 20, n. 3, p. 343–352, 2018.

ROCHA, J. E. C.; NOGUEIRA JUNIOR, M. R.; TAVARES JÚNIOR, I. S.; SOUZA, J. R. M.; LOPES, L.; SILVA, M. L. Configuração de redes neurais artificiais para relação hipsométrica de árvores de *Eucalyptus* spp. **Scientia Forestalis**, v. 49, p. e3706, 2021.

SCHIKOWSKI, A. B.; CORTE, A. P. D.; SANQUETTA, C. R.; Estudo da forma do fuste utilizando redes neurais artificiais e funções de afilamento. **Pesquisa Florestal Brasileira**, Colombo, v. 35, n. 82, p. 119–127, 2015.

SILVA, I. N.; SPATTI, D. H.; FLAUZIN, R. A. Redes neurais artificiais: para engenharia e ciências aplicadas. São Paulo: **Artliber**, v. 23, n. 5, p. 33–111, 2010.

SILVA, S.; OLIVEIRA NETO, S. N.; LEITE, H. G.; OBOLARI, A. M. M.; SCHETTINI, B. L. S. Avaliação do uso de regressão e rede neural artificial para modelagem do afilamento do fuste de eucalipto em sistema silvipastoril**. Enciclopédia Biosfera**, Goiânia, v. 13, n. 23, p. 189–199, 2016.

SOARES, F. A. A. M. N.; FLÔRES, E. L.; CABACINHA, C. D.; CARRIJO, G. A.; VEIGA, A. C. P. Recursive diameter prediction for calculating merchantable volume of *Eucalyptus* clones without previous knowledge of total tree height using artificial neural networks. **Applied Soft Computing**, v. 12, n. 8, p. 2030–2039, 2012.