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# Recursive diameter prediction and volume calculation of eucalyptus trees using Multilayer Perceptron Networks

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ABSTRACT

A major challenge in forest management is the ability to quickly and accurately predict bole volume of standing trees. This study presents a new model that uses Multilayer Perceptron (MLP) artificial neural networks for predicting tree diameters values. The model requires three diameter measures at the base of the tree, and recursively predicts other diameter measures. The predicted diameters allow for calculating tree volume using the Smalian method. The performance of the proposed model was satisfactory when compared with data obtained from tree scaling and volume equations.



## 1. Introduction

The extensive coverage of forests in Brazil, alongside with the huge supply chain involved from cultivation to product generation, denotes the great importance of forestry in that country. This results in an increased capacity to generate jobs and income in this economic sector. In 2001, statistics made by the Brazilian Society of Silviculture (SBS) indicated that the contribution of forestry to Brazil's gross domestic product reached US$ 11 billion, and exports were around US$ 4 billion. This generated about 2 million direct and indirect jobs. The forest cover of the Brazilian territory, combined with excellent soil and climatic conditions, indicate the great advantages of forestry in Brazil (Juvenal and Mattos, 2002).

Approximately 3 million hectares of planted forests in Brazil are of the genus *Eucalyptus*. Major investments by pulp and paper industries, combined with the efforts of research institutions and universities, have made that country one of the largest producers of eucalyptus in the world.

Eucalyptus is a fast-growing, low-cost tree species that produces more timber than other species. The yield of timber in Brazil is 45—50 $m^3$ $ha^{-1}$ $year^{-1}$. In Chile, USA, Canada and Finland, the yield is 20, 10, 7 and 4 $m^3$ $ha^{-1}$ $year^{-1}$, respectively (Votorantim Celulose e Papel – VCP, 2004).

The volume of timber planting is essential information in guiding rational and sustainable utilization of available forest resources. Thus it is very important to quantify it as precisely as possible. The most traditional method used by Brazilian timber companies are the use of volumetric equations. These equations are set with tree scaling samples when conducting forest inventory.

In volumetric equations, geometric assumptions are made about the tree shape. Such assumptions require various measures of diameters along the bole (trunk) for the construction of models that represent the stratum (sub-area) of the stand. Nevertheless, during the scaling, the sampled trees are felled. As this process must be repeated several times until all sections of the population are sampled, this task becomes very time-consuming and costly. Consequently, companies often overlook forest scaling data, which impairs predictions generated by volumetric equations (Andrade et al., 2006).

Other methods of estimating the bole volume are proposed by Smalian, Huber and Newton. These methods have been applied in the forestry sector since late eighteenth century (Finger, 1992; Machado and Figueiredo Filho, 2003; Scolforo, 2005).

From the 90's onwards, many researchers have used artificial neural networks (ANN) for approximating nonlinear functions. ANNs do not require any geometrical assumption on the function to be approximated. ANNs have been applied in many areas such

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as finance, time series forecasting, and pattern classification, among others.

Neural networks have been used in forest modeling to estimate several parameters such as tree diameter, height, volume and others. Guan and Gertner (1991) used ANNs to model growth and mortality of trees. In Leduc et al. (2001) ANNs were used to generate a probability distribution of DBH to classify the trees. Age, average height of dominant trees, trees per acre and site identifier were used as input data. Huang et al. (2009) used ANNs to find a frequency distribution of stem diameter classes based on the upper relative diameter, the average diameter and the diameter variation coefficient. Xiao et al. (1998); Brandão (2007); Ranson et al. (2007); Silva et al. (2008) predicted tree height based on the DBH, age and other statistical information using artificial neural networks. Diamantopoulou (2005b) predicted the diameter of fir trees using artificial neural networks. Bole diameter, the diameter at breast height and total tree height were used as input. The output of the network was all diameters between 5.3 and 33.3 at intervals of 4 m. The results were satisfactory, because fir trees are fairly regular. Nevertheless, around 90% of the samples had to be used for training, leaving only 10% for testing. In Diamantopoulou (2005a); Diamantopoulou (2006); Görgens (2006); Baleeiro (2007); Görgens et al. (2009); Silva et al. (2009); Özçelik et al. (2010) neural networks were used to estimate tree volume. In these studies, DBH and total height were used as input. A drawback of these studies is that trees with the same DBH and total height, but with different taper characteristics, resulted in equal volumes.

This work presents a new approach for predicting the diameters of eucalyptus trees by using Multilayer Perceptron Neural Network. We propose a recursive prediction of these diameters by taking into account only the measures of diameters at three different heights at the base of each tree. The predicted diameters allow us to calculate the tree bole volume through the Smalian method. Besides allow us to estimate these volumes by considering only three simple measures of each three, the present approach requires only 10% of the sampled trees for the training stage making the field work easier and faster.

The contribution of this paper is the recursive prediction of these diameters using with only three actual measurements taken at the base of the tree. The predicted diameters allow for calculating tree bole volume using the Smalian method. Moreover, the proposed model requires only 10% of the sampled trees for the training stage.

This paper is organized as follows. In Section 2 the recursive prediction model and the architecture of the MLP network are explained, where the most significant details are provided during training. The methods for calculating volume, volumetric equations and validation methods are also explained. Section 3 presents details on the performance of the proposed model and that of traditional methods. Finally, Section 4 presents the conclusions of this study.

## 2. Prediction methods and artificial neural networks

### 2.1. Prediction

Series prediction is commonly used for time series. That may be regarded as a modeling problem. For the prediction, a model is built between the inputs and outputs. This model is used to predict subsequent values based on previous values. Direct prediction and recursive prediction are some of the methods used for long-term time series forecasting (Ji et al., 2005).

#### 2.1.1. Direct prediction

To predict the values of a series, $M+1$ different models are built according to Eq. (1).

$$\hat{d}_{i+m} = f_m(d_{i-1}, d_{t-2}, \ldots, d_{i-n}), \qquad (1)$$

where $m = 0, 1, \ldots, M$; $M$ is the maximum horizon of prediction and $n$ is the size of the regressor which in turn is formed by the input variables of the right side of the equation.

Input variables on the right side of Eq. (1) form the regressor.

A satisfactory result was obtained by Diamantopoulou (2005b) by using Multilayer Perceptron Neural Network to predict directly the diameters of fir trees that are fairly regular ones.

#### 2.1.2. Recursive prediction

Recursive prediction can be constructed by first making a one step ahead prediction, according to Eq. (2).

$$\hat{d}_i = f(d_{i-1}, d_{i-2}, \ldots, d_{i-n}), \qquad (2)$$

In order to predict the next value in the series, Eq. (2) is also used, but the first term in this equation is the result obtained from the previous step, as shown in Eq. (3).

$$\hat{d}_{i+1} = f(\hat{d}_i, d_{i-1}, d_{i-2}, \ldots, d_{i-n+1}). \qquad (3)$$

In this work, diameters of trees of genus *Eucalyptus* are recursively predicted using Multilayer Perceptron Neural Network. Thus, for the prediction, diameters $d_{1.3}, d_{0.7}$ and $d_{0.3}$ are used as input, and the network output is the predicted diameter $\hat{d}_{2.0}$. In the next step, the inputs are $\hat{d}_{2.0}$, $d_{1.3}$ and $d_{0.7}$ and the network output yields the predicted diameter $\hat{d}_{3.0}$. These steps are repeated at intervals of one meter along the stem until it reaches the total height of the tree.

### 2.2. Multilayer Perceptron (MLP) artificial neural network

A Multilayer Perceptron (MLP) Neural Network is composed of an input layer, one or more hidden layers and an output layer. The input signal propagates feed-forward through the network, layer after layer (Haykin, 1998). Fig. 1 shows the MLP used in this work.

Several activation functions may be used in the MLP (Haykin, 1998). The activation function used in this work for the hidden layer neurons and for the output layer neurons was the hyperbolic tangent, also known as the tan-sigmoid or tansig, defined in Eq. (4).

$$\varphi(a) = \tanh(a) = \frac{2}{(1 + \exp(-2a))} - 1 \qquad (4)$$

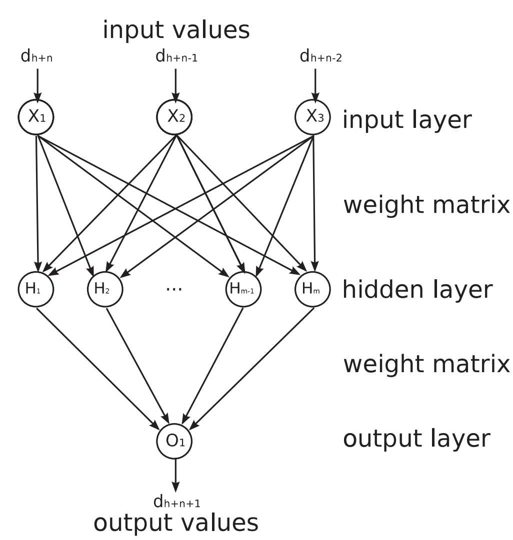


**Fig. 1.** Three-layer MLP architecture.

There are several MLP training algorithms, such as gradient descent, gradient descent with momentum, conjugate gradient, quasi-Newton, Levenberg–Marquardt, etc.

The Levenberg–Marquardt technique is more efficient than the conventional gradient descent technique (Hagan and Menhaj, 1994). The gradient descent technique is a steepest descent algorithm and involves small enough steps on the local gradient of the scalar field. One disadvantage of this method is the possibility that the gradient descent finds a local minimum before the global minimum is reached. The Levenberg–Marquardt algorithm is a refinement of the Gauss–Newton method, which is a variant of Newton's method (Levenberg, 1944; Marquardt, 1963). Newton's method uses information from the second order partial derivative of the performance index used to adjust the weights. Thus gradient information is used in conjunction with error surface curvature information.

In this study, all codes were written using MATLAB®. The MATLAB Neural Network Toolbox™ was used both to implement and to use the MLP and training algorithm (MATLAB, 2010).

### 2.3. Error calculation of diameters predicted by the MLP

In order to verify the behavior of the MLP in the prediction of all diameters of each tree, Root Mean Square Error ($\text{RMSE}_\%$) and linear correlation ($R$) were used, as shown in Eqs. (6) and (7) (Özçelik et al., 2010), respectively.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i^a - y_i^e)^2}{n}} \tag{5}$$

$$\text{RMSE}_\% = \left(\frac{\text{RMSE}}{\bar{y}^a}\right)100 \tag{6}$$

$$R = \frac{\sum_{i=1}^{n}\left[(y_i^a - \bar{y}^a)(y_i^e - \bar{y}^e)\right]}{\sqrt{\sum_{i=1}^{n}(y_i^a - \bar{y}^a)^2}\sqrt{\sum_{i=1}^{n}(y_i^e - \bar{y}^e)^2}} \tag{7}$$

where $y^a$ and $y^e$ are the vectors of actual diameters and estimated, respectively, $\bar{y}^a$ and $\bar{y}^e$ are the averages of the actual and estimated diameters values, respectively, and $n$ is the number of diameter measures between input measures and the total height.

### 2.4. Tree volume calculation from estimated diameters and using volumetric equations

The volumes of all trees are calculated using the Smalian method, according to Eqs. (8) and (9), in order to verify the efficiency of the MLP network model proposed. These volumes are compared with volumes calculated with actual diameters using Smalian Method and obtained through the Schumacher and Hall (log) method.

The Schumacher and Hall (log) model is a volumetric equation that estimates tree volume from the DBH and total height ($H_t$), according to Eq. (10). This model is adjusted using parameters obtained from accurately measured trees (Cabacinha, 2003).

$$g_i = \frac{(d_i/2)^2\pi}{10,000} \tag{8}$$

$$v = \sum_{i=1}^{n-1}\frac{g_i + g_{i+1}}{2}l_i + \frac{g_n l_n}{3} \tag{9}$$

where $v$ is the total tree volume, $g_i$ is the basal area of the $i$th position, $l_i$ is the section length of the $i$th position, $g_n$ is the basal area of the cone (tree tip), $l_n$ is the length of the cone and $d_i$ is the diameter of the ith position. In Eq. (8) the area of each $g_i$ is divided by 10,000 to convert from $cm^2$ to $m^2$.

$$\log v = \beta_0 + \beta_1 \log \text{DBH} + \beta_2 \log H_t + \varepsilon \tag{10}$$

where $v$ is the volume, DBH is the diameter at breast height and $H_t$ is the total height. The tree volume is obtained using the exponential of the result of Eq. (10).

### 2.5. Error calculation of predicted volumes

In order to verify the accuracy of the volumes calculated from the diameters predicted by the MLP, the following percentage errors were calculated: mean deviation Precision ($P_\%$)(Freese, 1960), ($\text{MD}_\%$), Bias ($Bias_\%$)(Leite and Andrade, 2002), Root Mean Square Error ($\text{RMSE}_\%$) and linear correlation ($R$) Özçelik et al., 2010), according to Eqs. (11), (12), (13), (6) and (7), respectively.

$$P_\% = \sqrt{\frac{1.96^2}{\chi_n^2}\sum_{i=1}^{n}\left(\frac{y_i^a - y_i^e}{y_i^a}\right)100} \tag{11}$$

$$\text{MD}_\% = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i^e - y_i^a}{y_i^a}\right)100 \tag{12}$$

$$\text{Bias}_\% = \frac{\sum_{i=1}^{n}y_i^e - \sum_{i=1}^{n}y_i^a}{\sum_{i=1}^{n}y_i^a}100 \tag{13}$$

where $y^a$ and $y^e$ are the actual and estimated volumes, respectively, $n$ is the number of $y^a$ and $y^e$ pairs, $\bar{y}^a$ and $\bar{y}^e$ are the averages of actual and estimated volumes, respectively; 1.96 is the value of the normal standard deviation for a bilateral probability of 0.05; $\chi_n^2$ is the chi-square value for $n$ degrees of freedom.

All statistics data calculated for the volumes obtained using Smalian formula with the diameters estimated by MLP were also calculated for the volumes obtained using the Schumacher and Hall (log) method.

The statistics were summed to assess the performance of the MLP in comparison with the Schumacher and Hall method (log). We performed the difference $(1 - R)$ to show how the data are uncorrelated, and this difference value was added to the sum of statistics multiplied by 100. Since the goal of this sum is to show each method's error in relation to the actual volumes, the smaller this result, the better the performance of the method being analyzed (Andrade, 2001). The sum of statistics is calculated as shown in Eq. (14).

$$\text{Total}_\% = \text{MD}_\% + \text{Bias}_\% + 100\cdot(1 - R) + P_\% + \text{RMSE}_\% \tag{14}$$

where $\text{Total}_\%$ is the sum of statistics, $\text{MD}_\%$ is the mean deviation, $\text{Bias}_\%$ is the bias, $R$ is the linear correlation, $P_\%$ is the precision, and $\text{RMSE}_\%$ is the Root Mean Square Error. All of these statistics are percentages.

In order to check whether there are statistical accuracy differences between the MLP and the Schumacher and Hall model (log), a two-way analysis of variance (ANOVA) was performed.

To check whether the data met the assumptions for performing the ANOVA we performed the Lilliefors test to ensure normality and the Cochran test to check homogeneity of variances. These tests were performed considering a significance level of 5%.

The parameters considered for the ANOVA were the volumes calculated using actual tree diameters (measured in the field), the volumes predicted by the MLP and the volumes calculated by the Schumacher and Hall model (log). This analysis was performed for each data separately (training and test) and jointly (train + test). In calculating the ANOVA, the diameter classes were used as control.

In ANOVA, the null hypothesis ($H_0$) considers that the methods being analyzed are statistically equivalent. If the probability ($p$) is smaller than 0.05 the ANOVA's null hypothesis ($H_0$) can be discarded, otherwise there are no statistical differences between the methods.

## 3. Results and discussion

Several tests were carried to determine which MLP structure was the most adequate for predicting tree diameters. At the beginning, we adopted the amount of five neurons in the hidden layer. Then, this value was increased in each test until there were no significant improvement in the values of $RMSE_{\%}$ and $R$. The stabilization of these values was reached for 20 neurons in the hidden layer. Besides this value, the most adequate structure for the MLP network obtained by us took into account an input layer with three variables representing three diameter measures and an output layer with one neuron which yields an estimated diameter value.

### 3.1. Data

The data used in this study were acquired from a stand in the city of Aracruz, in the state of Espírito Santo, Brazil. A total of 615 trees of the genus *Eucalyptus* were used, obtained from the same clonal genetic material. All the trees were the same age (six years and six-months-old), planted with spacing 3×3 m, distributed in 16 circular plots of 360 m$^2$. These trees were felled and scaled rigorously by the Smalian method (Cabacinha, 2003). Diameters were measured with a caliper, at heights: 0.30; 0.70; 1.30; 2.00 m from the ground, then at regular intervals of 1 m. The diameter at the tip of the tree is considered to be zero. The diameters at heights $h_{0.3}$ and $h_{1.3}$ are known as the stump diameter and the Diameter at Breast Height (DBH), respectively. Fig. 2 illustrates how the trees were measured.

Several characteristics of the trees vary according to the DBH. Because of this, several papers in the literature have separated trees in diameter classes of amplitudes 4 and 5 cm based on the DBH (Schneider et al., 1996; Pires and Calegario, 2007). In this work, trees were separated in five classes at intervals of 3 cm according to the DBH values, and for each of these classes an MLP network was used for training and prediction. Class 5 was the only one that was extended in order to include a single tree that was isolated. Table 1 shows, for each diameter class, the number of trees and statistical data for DBH and total tree height.

The MLP model proposed in this paper was based on the relationship between the three neighboring diameters used as input, and the next diameter that is predicted as the output of the network. In order to verify the relationship of one diameter measure with their neighboring diameters, the autocorrelation coefficient was calculated using the linear correlation Equation (Eq. (7)). In autocorrelation $y^a$ is the vector of actual diameter and $y^e$ is the same vector shifted, $\bar{y}^a$ and $\bar{y}^e$ are the averages of the actual diameters and $n$ is the number of diameter measures between input measures and the total height. Autocorrelation coefficients were calculated for each tree with 1–3 shifts. Table 1 shows the lowest and highest autocorrelation coefficients for one shift in each class.

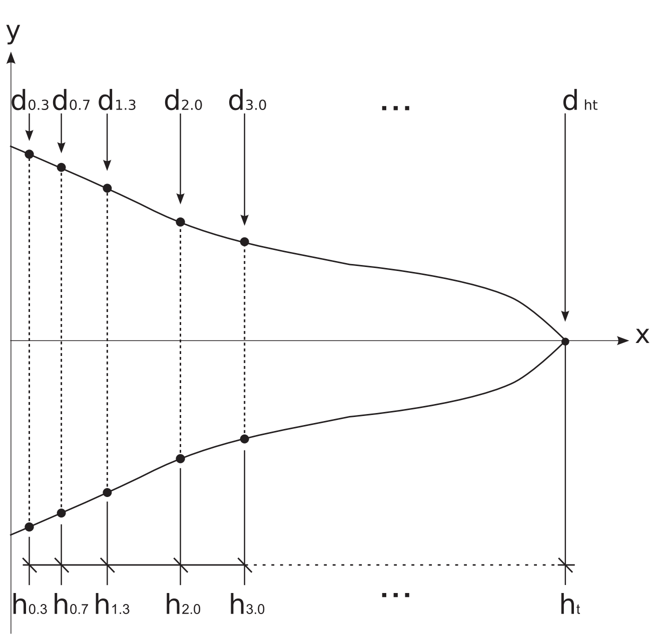


**Fig. 2.** Heights measured and their diameters.

Results from autocorrelation tests with one shift showed large values. It can be observed in Table 1 that the lowest and highest autocorrelation for one interval were 0.63 and 0.90, respectively. Whereas for tests with three intervals, the lowest and the highest autocorrelation values were 0.55 and 0.81. Therefore the tests proved that there is a strong relationship between the three neighboring diameters and the next predicted diameter.

For greater reliability and speed when training the MLP, tree diameter data were normalized within the range $[-1,1]$, using Eq. (15). In this range, $-1$ represents a diameter of 0, 1 represents the largest diameter, and all the other diameters lie within these values (Zanchettin and Ludermir, 2005). Normalization was done for all trees regardless of their class.

$$X_{\text{NORM}} = (b-a)\cdot\left(\frac{X-\min(X)}{\max(X)-\min(X)}\right)+a \tag{15}$$

where $X_{\text{NORM}}$ is the value of the normalized diameter, $X$ is the tree diameter, $\min(X)$ is the smallest tree diameter, $\max(X)$ is the largest tree diameter, $a = -1$ and $b = 1$ define the normalization range.

After the MLP predicted the diameters, diameter values were denormalized using the $\min(X)$ and $\max(X)$ values, which were previously used for normalization.

The algorithm used for training the MLP was the Levenberg–Marquardt (Marquardt, 1963) with 1.000 epochs. Training of the MLP was performed with random initial weights, and no adaptive learning rate and momentum parameters were used.

In order to avoid overfitting, we used an heuristic that was to establish the mean square error (*MSE*) as $1\times10^{-10}$ and train the MLP until there no exists any significant reduction or increase in the five consecutive epochs. In the tests, MLP converged before 150 epochs.

Table 2 shows *MSE* values and the average number of epochs until convergence for each tree class.

For training the MLP, 10% of trees or at least 10 trees were randomly selected from each class, to collect input and output sample sets. Each of the selected trees produces input samples $[d_{i-2}, d_{i-1}, d_i]$ and output sample $[d_{i+1}$. For example, for training the network, the input-output pair was $[d_{0.3}, d_{0.7}, d_{1.3}]$ and $[d_{2.0}]$, where $d_{0.3}, d_{0.7}, d_{1.3}$ and $d_{2.0}$ represent distances 0.3, 0.7, 1.3 and 2.0, measured from the ground up, in meters. The next input-output pair was $[d_{0.7}, d_{1.3}, d_{2.0}]$ and $[d_{3.0}]$, where $d_{3.0}$ is the distance of 3.0 meters measured from the ground up, and so on.

In the testing phase of the MLP, only initial diameter measures $d_{0.3}, d_{0.7}$ and $d_{1.3}$ are used to predict the remaining diameter measures of each tree. This phase is performed for each tree individually, according to the recursive prediction procedure described by Eq. (3). Therefore, these initial measures are used to predict diameter $d_{2.0}$. Then, measures $d_{0.7}$, $d_{1.3}$ and the predicted measure $d_{2.0}$ are used to predict measure $d_{3.0}$, and so on. This procedure is described in Tables 3 and 4 shows the definitions used in this algorithm.

### 3.2. Diameter Prediction

Due to the large number of trees involved in the study, Table 5 outlines $RMSE_{\%}$ and Correlation% ($R$) values produced by the testing phase of the tree diameter prediction.

**Table 1**
Descriptive statistics of eucalyptus trees and autocorrelation.

| Class | $n$ | Autocorr | | DBH (cm) | | | | | Total height ($H_t$) (m) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Var | SD | Min | Max | Mean | Var | SD | Min | Max |
| 1 | 14 | 0.63 | 0.84 | 8.68 | 0.95 | 0.97 | 7.15 | 10.10 | 17.60 | 3.49 | 1.87 | 14.20 | 19.70 |
| 2 | 106 | 0.77 | 0.87 | 12.01 | 0.54 | 0.73 | 10.32 | 13.14 | 22.83 | 2.75 | 1.66 | 18.00 | 26.70 |
| 3 | 302 | 0.78 | 0.89 | 14.62 | 0.68 | 0.82 | 13.15 | 16.14 | 25.74 | 1.57 | 1.25 | 18.40 | 29.40 |
| 4 | 178 | 0.83 | 0.90 | 17.23 | 0.64 | 0.80 | 16.15 | 19.14 | 27.52 | 1.39 | 1.18 | 24.20 | 30.10 |
| 5 | 15 | 0.82 | 0.90 | 20.21 | 1.70 | 1.31 | 19.31 | 24.55 | 29.23 | 1.06 | 1.03 | 27.20 | 30.60 |

**Table 2**
Training phase samples and parameters.

| Class | Total | | Samples | | Train | |
|---|---|---|---|---|---|---|
| | Trees | Sets | Trees | Sets | Epochs | MSE |
| 1 | 14 | 231 | 10 | 155 | 35 | $3.0 \times 10^{-4}$ |
| 2 | 106 | 2405 | 11 | 239 | 45 | $3.0 \times 10^{-4}$ |
| 3 | 302 | 8025 | 31 | 792 | 120 | $3.5 \times 10^{-4}$ |
| 4 | 178 | 5105 | 18 | 498 | 110 | $3.5 \times 10^{-4}$ |
| 5 | 15 | 462 | 10 | 298 | 130 | $5.0 \times 10^{-4}$ |
| Total | 615 | 16228 | 80 | 1982 | – | – |

As shown in Table 5, for tree classes 1 and 5, which contain a small number of trees, the largest RMSE$_{\%}$ value is less than 10%. And for classes 2, 3 and 4, which contain a much larger number of trees than classes 1 and 5, the highest value of RMSE$_{\%}$ is around 22%. Although the latter figure is large, the average of RMSE$_{\%}$ (errors) for classes 2, 3 and 4 was around 7%, which shows that the diameters predicted by the MLP are very close to the actual diameters measured in the trees. This table also shows the lowest and highest linear correlation coefficients between predicted and measured diameters. Virtually all of these coefficients are within the range from 0.97% to 0.99%. This indicates that there is a very strong linear correlation between the actual measured diameters and the ones predicted by the MLP.

**Table 3**
Formal statement of the prediction algorithm.

| | |
|---|---|
| $X$ | Vector of inputs of MLP |
| $X_1$ | Input 1 of MLP |
| $X_2$ | Input 2 of MLP |
| $X_3$ | Input 3 of MLP |
| $i$ | The height that is being predicted |
| $d_{0.3}$ | Diameter at the height 0.3 m (stump diameter) |
| $d_{0.7}$ | Diameter at the height 0.7 m |
| $d_{1.3}$ | Diameter at the height 1.3 m (diameter at breast height – DBH) |
| $D$ | Set of predicted diameters |
| | The diameter at the tip of the tree is considered to be zero |
| $D_i$ | Diameter at the height $i$ |
| $H_t$ | Total tree height |

**Table 4**
Tree prediction algorithm.

**function** *PredictTree*$(d_{0.3}, d_{0.7}, d_{1.3}, H_t)$
$X \leftarrow [d_{0.3}, d_{0.7}, d_{1.3}]$
$D \leftarrow [\,]$
$i \leftarrow 2.0$
WHILE $i < H_t$ **do**
  $D_i \leftarrow Net.PredictDiameter(X)$
  $X_1 \leftarrow X_2$
  $X_2 \leftarrow X_3$
  $X_3 \leftarrow D_i$
  $i \leftarrow i + 1.0$
**end while**
**return** $D$
**end function**

**Table 5**
Diameter prediction error per class – RMSE$_{\%}$ (largest, smallest, average and standard deviation) and correlation (smallest, largest).

| Class | Trees | RMSE$_{\%}$ | | | | Correlation ($R$) | |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Avg | SD | Min | Max |
| 1 | 4 | 3.05 | 9.98 | 6.21 | 3.40 | 0.98 | 0.99 |
| 2 | 95 | 1.83 | 22.94 | 7.31 | 4.20 | 0.98 | 0.99 |
| 3 | 271 | 1.69 | 21.37 | 6.68 | 3.70 | 0.97 | 0.99 |
| 4 | 160 | 1.67 | 22.83 | 7.41 | 4.43 | 0.99 | 0.99 |
| 5 | 5 | 2.07 | 6.21 | 4.35 | 1.65 | 0.99 | 0.99 |

Fig. 3a, b, d, e, g, h, j, k, m and n shows with solid and dotted lines, respectively, the values of actual diameters and the diameters predicted by the MLP. And Fig. 3c, f, i, l and o illustrates the histograms of the RMSE$_{\%}$ calculated for each tree in each class.

Fig. 3a, d, g, j and m shows the lowest RMSE$_{\%}$ for each class. It can be observed in these figures that the values of the actual diameters and those predicted by the MLP are considerably coincident with each other. It also shows that the MLP have a high approximation for cases in which the trees have a linear profile, and even when the tree profile is nonlinear the MLP satisfactorily tracked abrupt changes in diameter.

The largest RMSE$_{\%}$ are shown in Fig. 3b, e, h, k and n. These figures show that the MLP have underestimated the actual diameter values for all classes except for class 5, where there was a slight overestimation of the diameters.

Although Fig. 3 illustrates the predicted and actual diameters of a few trees, the behavior of all the trees used for testing showed that the MLP had difficulty in predicting diameters closer to the treetops. This was expected since the model proposed in this paper performs recursive predictions and the error in a given diameter will be passed on to the next predicted diameter. Therefore, the more recursive predictions are made, the higher the difference between actual and predicted diameters will be. However, this difference has a very small influence on the calculation of each tree volume.

Fig. 3c, f, i, l and o, shows the histograms of RMSE$_{\%}$ for each class. These figures show that most RMSE$_{\%}$ values are below 10% for classes 2, 3 and 4, which is a very good result. As the amount of test trees in classes 1 and 5 is very small, there is no accumulation of RMSE$_{\%}$ around the mean, but all RMSE$_{\%}$ values are below 10% and 6.3% for classes 1 and 5, respectively, which are also very suitable values.

### 3.3. Comparison between tree volumes calculated using actual and predicted diameters and volumes estimated using the Schumacher and Hall method (log)

The Smalian equation (Eq. (9)) is used to calculate tree volumes based on both actual diameters and those predicted by the MLP, and the Schumacher and Hall model (log) estimates these volumes

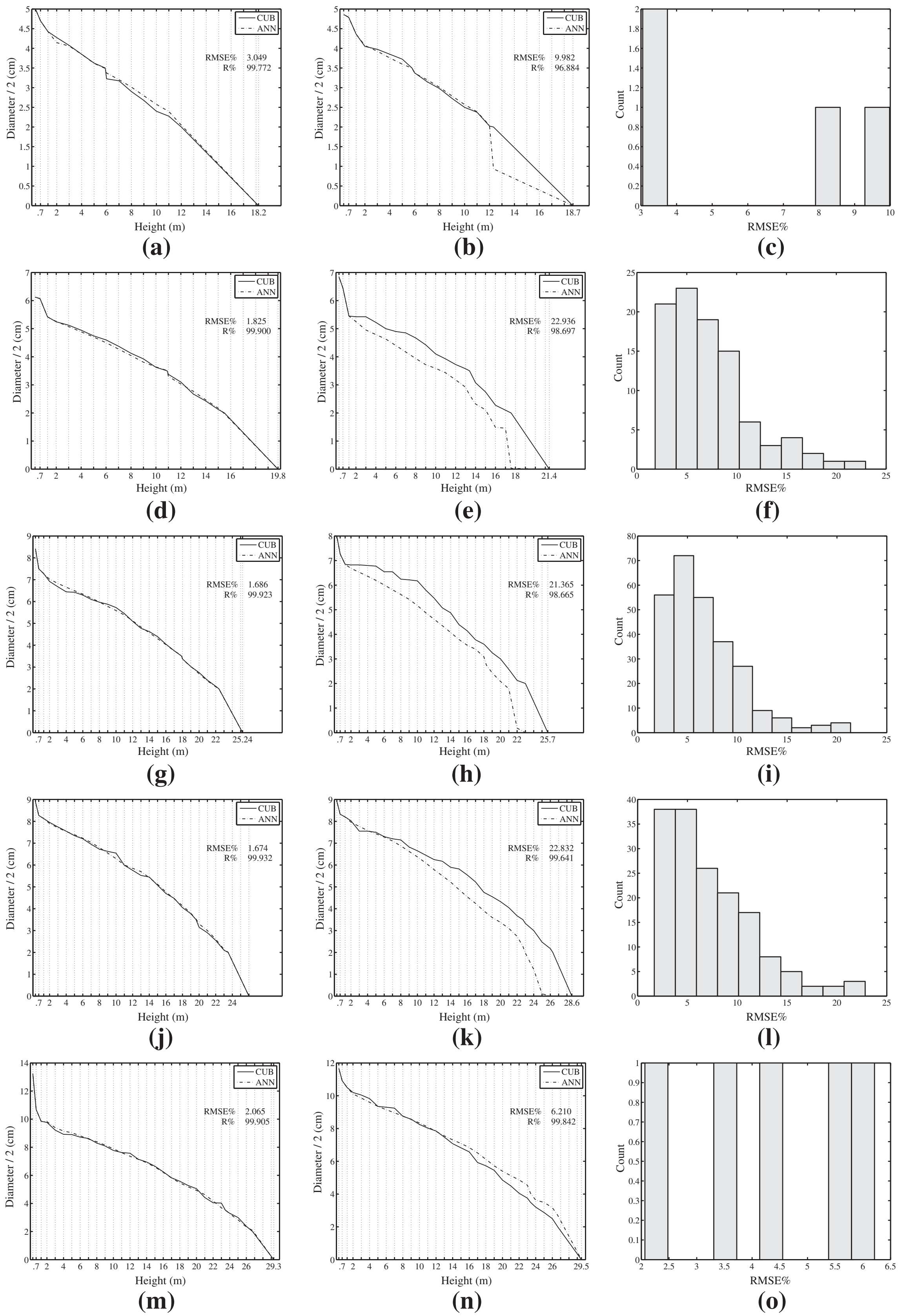


**Fig. 3.** Prediction example curves (best and worst case) and RMSE$_{\%}$ histogram per class.

with Eq. (10). To obtain the volume from Eq. (10) it is necessary to apply the exponential on both sides of it.

The values used for the $\beta$'s and the $\varepsilon$ for calculating tree volume using the Schumacher and Hall model (log) (Eq. (9)) are

**Table 6**
Calculated volumes using actual diameters, diameters predicted by the MLP and predicted by the Schumacher and Hall method (log).

| Class | Real | MLP | Schumacher and Hall (log) |
|---|---|---|---|
| (a) *Volumes of trees used in the training phase of the MLP* | | | |
| 1 | 0.4268 | 0.4265 | 0.4318 |
| 2 | 1.2513 | 1.2551 | 1.2464 |
| 3 | 6.6344 | 6.6348 | 6.5809 |
| 4 | 5.3274 | 5.3347 | 5.3945 |
| 5 | 4.2240 | 4.3165 | 4.4264 |
| Total | 17,8639 | 17.9676 | 18.0800 |
| (b) *Volumes of trees used in the testing phase of the MLP* | | | |
| 1 | 0.2293 | 0.2321 | 0.2319 |
| 2 | 11.5382 | 11.3273 | 11.4700 |
| 3 | 55.2320 | 54.2328 | 54.6750 |
| 4 | 47.7756 | 48.0092 | 48.3938 |
| 5 | 2.2226 | 2.2007 | 2.2382 |
| Total | 116.9977 | 116.0021 | 117.0089 |
| (c) *Total volumes of trees used in the training and in the testing phase of the MLP* | | | |
| 1 | 0.6561 | 0.6585 | 0.6636 |
| 2 | 12.7896 | 12.5823 | 12.7164 |
| 3 | 61.8663 | 60.8675 | 61.2559 |
| 4 | 53.1030 | 53.3438 | 53.7882 |
| 5 | 6.4466 | 6.5172 | 6.6646 |

$\beta_0 = -10.79449927$, $\beta_1 = 1.942384069$, $\beta_2 = 1.226015699$ and $\varepsilon = 0$. Parameters $(R^2_{\%}) = 99.44$, residual standard error $(S_{yx}) = 0.011993$, and $(S_{yx\%}) = 5.81$ confirm that in fact these values of $\beta$ and $\varepsilon$ are appropriate to estimate the volumes of the trees examined in this paper (Cabacinha, 2003).

Table 6 shows tree volumes aggregated by classes. These are volumes that were either calculated using actual diameters and diameters predicted by the MLP, or estimated by the Schumacher and Hall model (log). This table is divided into Table 6a–c. Each of these tables contains volumes that were obtained from actual diameters, volumes that were obtained from diameters predicted by the MLP, and volumes that were estimated by the Schumacher and Hall method (log). The calculation of the volumes in Table 6a was done with the trees used in the training phase of the MLP. Table 6b shows the volumes calculated with the trees used in the testing phase of the MLP. Table 6c shows the sum of the volumes of Tables 6a and b.

Tables 6a–c shows that there is a very small difference between the volumes calculated using actual diameters, the volumes calculated using diameters predicted by the MLP, and the volumes estimated by the Schumacher and Hall method (log). In some cases these differences are within the first, second and third decimal places. In a few cases these differences were within the integer part of the volume value, and when these occurred the difference was no greater than one.

As seen in Table 6c, the percentage difference between total volumes calculated using actual diameters and diameters predicted the MLP was 0.66%; and the difference between volumes calculated using actual diameters and volumes estimated by the Schumacher and Hall method (log) was 0.17%. Therefore, the percentage difference between actual data and values predicted by the MLP and values estimated by the Schumacher method is less than 1%.

Table 7 shows volume estimation error statistics per class.

As seen in Table 7 the sums of the statistics $(\text{Total}_{\%})$ of volumes estimated using the MLP were better for classes 1 and 5 and were worse for classes 2, 3 and 4 in comparison to the Schumacher and Hall method (log). The main reason these results are worse was due to a smaller linear correlation. This shows that volumes estimated with the MLP have a slightly larger range than the volumes estimated by the Schumacher and Hall method (log). These variations can be observed in Fig. 4, where volume results estimated by the MLP are slightly more scattered than the volumes estimated by the Schumacher and Hall method (log) for classes 2, 3 and 4.

Fig. 4 shows the scatter plots by class between actual volumes and volumes estimated by the MLP and estimated by the Schumacher and Hall method (log). Fig. 4 a, c, e, g and i shows the scatter plots between the actual volumes and volumes estimated by the MLP, for classes 1 through 5, respectively. Fig. 4b, d, f, h and j shows the scatter plots between the actual volumes and the volumes estimated by the Schumacher and Hall method (log), for classes 1 through 5, respectively.

By comparing the scatter plots per class between actual volumes and volumes estimated by the MLP and volumes estimated by the Schumacher and Hall method (log), it can be observed that data from both estimation methods are not very scattered. Data relative to the Schumacher and Hall method (log) are slightly less scattered for classes 2, 3 and 4, in comparison with the MLP; however, this scatter difference between these methods is not significant when calculating total volume for the forest inventory.

The Lilliefors and Cochran test revealed normality and homogeneity of variances ($p < 0.05$), so the ANOVA could be used in data analysis.

The 2-way ANOVAs performed for data sets train, test and train + test yielded results of values $p = 0.5568$; 0.5575 and 0.5362, respectively. Because these three values were greater than 0.05 then the null hypothesis ($H_0$) cannot be rejected, i.e. there are no statistical differences between results from the MLP and from the Schumacher and Hall method (log).

## 4. Conclusions

In order to predict tree diameters using MLP network, only three measures of actual diameters are required to be taken for each tree at its base. Tree scaling data from approximately 10% of trees selected from the population are required for the training phase of the MLP; total training time for the established MSEs was 30 s on average, and total time for prediction was 15 min. For conducting forest inventory using traditional volumetric equations, many trees from the stand must be felled and scaled, and the

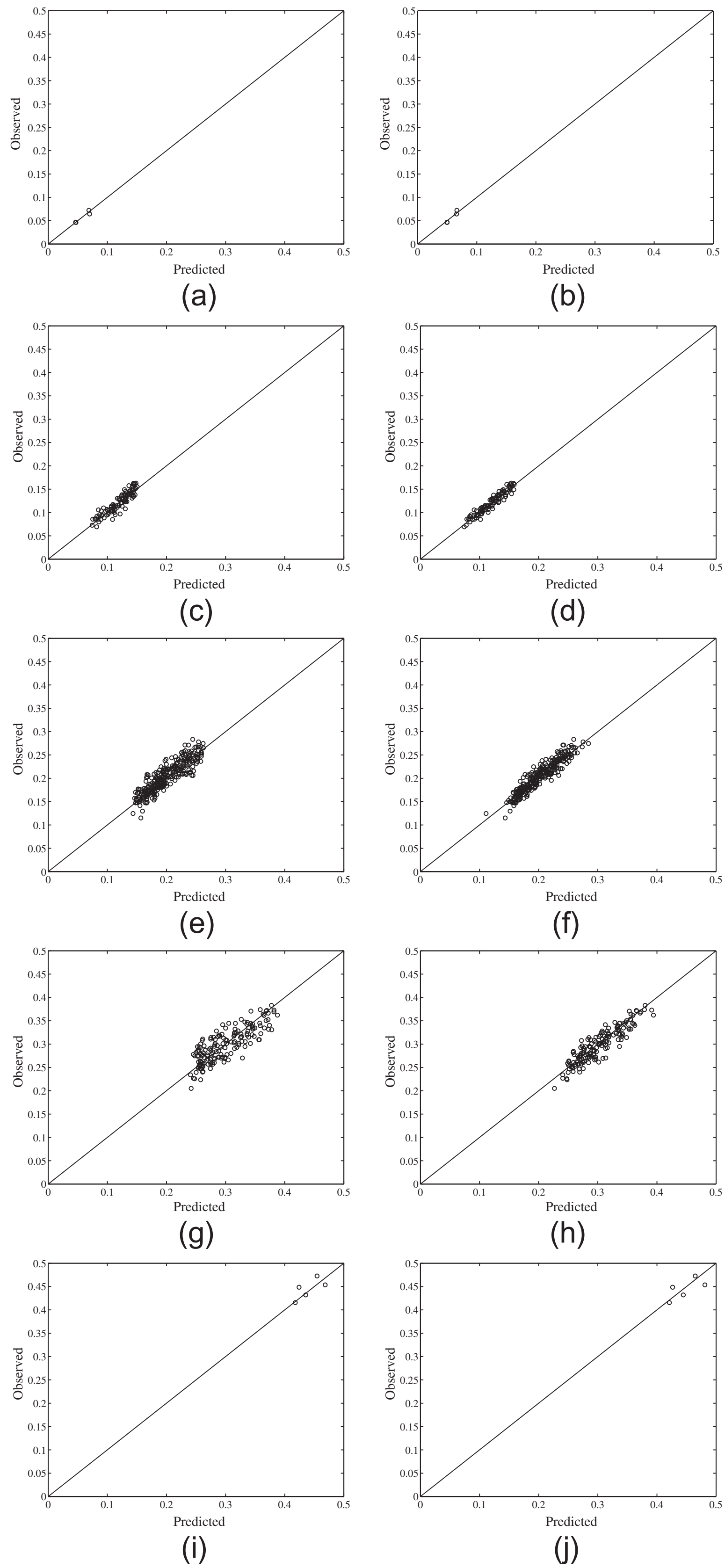


**Fig. 4.** Scatter plot: ANN and Schumacher and Hall (log) per classes.

time taken until such task is completed is much longer than the time taken by the MLP model.

Two-way ANOVA between volumes calculated from actual diameters, volumes calculated from diameters predicted by the

**Table 7**
Comparison between actual and estimated tree volumes. (a) volumes predicted by the MLP. (b) volumes predicted by the Schumacher and Hall method (log).

| *Class* | $MD_{\%}$ | $Bias_{\%}$ | $100 \cdot (1 - R)$ | $P_{\%}$ | $RMSE_{\%}$ | $Total_{\%}$ |
|---|---|---|---|---|---|---|
| (a) | | | | | | |
| 1 | 3.9894 | 1.2144 | 4.1807 | 2.3409 | 5.8582 | 17.5836 |
| 2 | 6.6449 | 1.8284 | 8.3449 | 4.8106 | 8.0537 | 29.6825 |
| 3 | 6.1972 | 1.8091 | 11.2285 | 6.3584 | 7.8044 | 33.3976 |
| 4 | 6.3542 | 0.4888 | 17.9737 | 7.2854 | 7.6585 | 39.7606 |
| 5 | 2.7671 | 0.9884 | 28.8029 | 5.2218 | 3.4181 | 41.1983 |
| (b) | | | | | | |
| 1 | 6.3031 | 1.1362 | 2.6441 | 1.8626 | 6.7277 | 18.6737 |
| 2 | 4.8995 | 0.5910 | 4.2317 | 3.4372 | 5.6565 | 18.8159 |
| 3 | 4.5143 | 1.0083 | 5.9751 | 4.6406 | 5.6960 | 21.8343 |
| 4 | 4.3388 | 1.2938 | 8.9151 | 5.2019 | 5.2948 | 25.0444 |
| 5 | 3.3728 | 0.6981 | 31.5281 | 3.1508 | 3.8846 | 42.6344 |

MLP and volumes estimated by volumetric equations showed that there is no statistical difference between these volumes.

Results obtained with MLP were quite satisfactory for predicting tree diameter. Thus, use of this model can be recommended to aid automating the forest inventory process, as it significantly reduces cost and time for completing the inventory. Moreover, this approach is less susceptible to human error during the forest inventory process.

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