

## Computational analysis of resilient propagation algorithm variants for predicting harvester productivity

Gianmarco Goycochea Casas<sup>1\*</sup>, Arthur Araújo Silva<sup>1</sup>, Zool Hilmi Ismail<sup>2</sup>, Pedro Henrique Guimarães Abrantes Lacerda<sup>1</sup>, Bruno Leão Said Schettini<sup>1</sup> and Hélio Garcia Leite<sup>1</sup>

<sup>1</sup>Department of Forest Engineering, Federal University of Viçosa, 36570-900 Viçosa, MG, Brazil

<sup>2</sup>Center for Artificial Intelligence and Robotics, Universiti Teknologi Malaysia, 54100 Jalan Sultan Yahya Petra, Kuala Lumpur, Malaysia

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### ✉ \* CORRESPONDING AUTHOR

Gianmarco Goycochea Casas  
Department of Forest Engineering,  
Federal University of Viçosa, 36570-  
900 Viçosa, MG, Brazil  
Email: gianmarco.casas@ufv.br

### ABSTRACT

This study investigated the use of artificial neural networks (ANNs) to estimate the productivity of forestry harvesters operating in commercial eucalyptus plantations in Brazil. The dataset, collected from mechanised harvesting operations over continuous 24-hour shifts in the states of Espírito Santo and Bahia, included quantitative and categorical variables. Quantitative inputs comprised the mean individual tree volume and productivity. Categorical variables included terrain inclination, tree tortuosity and bifurcation, sub-forest presence, operator experience, and type of service supply. Four variants of the Resilient Propagation (Rprop) algorithm were evaluated: Rprop+, iRprop+, Rprop-, and iRprop-. A total of 200 ANN models (50 per variant) were trained using 70% of the data, with the remaining 30% reserved for validation. All networks employed min-max normalisation, sigmoid activation functions, and an eight-neuron hidden layer. Model performance was assessed using the correlation coefficient (R), root mean square error percentage (RMSE%), bias percentage, and variance. The Rprop+ variant achieved the best predictive performance, with  $R = 0.837$ ,  $RMSE\% = 18.380$ ,  $bias\% = -0.017$ , and  $variance = 9.867$ , proving high reliability in modelling harvester productivity and offering valuable support for planning and decision-making in mechanised forestry operations.

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## 1. INTRODUCTION

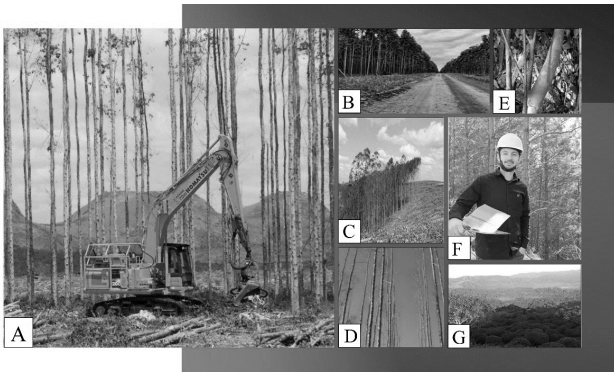
In 2024, the Brazilian forestry sector reached a milestone by surpassing 10.2 million ha of cultivated tree plantations. Eucalyptus remained the dominant species, covering 7.8 million ha (76%), followed by pine with 1.92 million ha (19%). Other species, including acacia, teak, rubber tree, and araucaria, occupied approximately 0.5 million ha of agricultural land. The state of Minas Gerais continued to lead with 2.26 million ha of planted forests, followed by Mato Grosso do Sul (1.35 million ha) and São Paulo (1.28 million ha). These plantations are primarily established in previously degraded or low-productive areas, contributing to sustainable land recovery (IBÁ, 2024). Among the products derived from the raw material are pulp, paper (packaging paper, toilet paper, writing, and printing paper), furniture, and energy (charcoal, pellets). This industry contributes to 6.9% of the Gross Domestic Product (GDP) in Brazil, and is currently the largest producer of charcoal and the second largest producer of pulp in the world (FAOSTAT, 2022).

The remarkable growth of Brazil's forestry sector is driven by a strong pipeline of planned investments, now surpassing R\$ 105 billion (approximately USD 18.9 billion) through 2028. This development reflects the resilience of this sector amidst rising global demand for sustainable products and is supported by advanced technologies and responsible forest management practices (IBÁ, 2024). Under this scenario, a growth in demand for timber in the coming years is expected, and investors will face new challenges in forestry harvesting to maintain a high productivity, such as difficulties of terrain slope, growth, tree production and shape, database management, and forest harvesting automation. Thus, there is an urgent need for advanced technological innovation for the processing of the database, information, and digital services (Campos, 2021).

In Brazil, various technologies have been incorporated for mechanised forest harvesting tailored to their needs, particularly harvester and forwarder tractors (Silva, 2021). Among the most widespread systems in Brazil, the cut-



productivity and average individual volume (Table 2). These variables were selected due to the substantial influence on harvester logging activity based on field analysis and discussion among forest machine operators and specialists.



**Figure 2:** Categorical variables influencing forestry harvester performance for modelling productivity (A) Flat ground (B), Sloping ground (C), Normal tree (D), Tree tortuosity and bifurcation (E) Operator experience time and service supply (F) Presence of sub-forest (G) Forest landscape.

**Table 1:** Categorical variables used in the analysis of factors affecting forestry harvester performance.

Variable	Categories
Tortuosity and bifurcation	Yes, No
Land Inclination	Sloping, Flat ground
Presence of sub-forest	Yes, No
Operator experience	≥ 1 year
Service supply	Outsourced, under test, owner

**Table 2:** Descriptive statistics of quantitative variables related to forestry harvester performance.

Variable	Mean	Std. Error	Std. Dev.	Min	Max	95% Confidence Level
Mean individual volume (m <sup>3</sup> )	0.1600	0.0014	0.0548	0.0301	0.3909	0.0027
Productivity (m <sup>3</sup> ·h <sup>-1</sup> )	17.0967	0.1496	5.9634	4.6250	46.4820	0.2935

## 2.2. Fitting the database using ANN

A productivity function (P) in m<sup>3</sup>·h<sup>-1</sup> was established as the output variable and modelled in relation to mean individual volume (MIV) in m<sup>3</sup>, terrain inclination (TI), tortuosity/bifurcation (T/B), sub-forest presence (SFP), operator experience (OE), and service supply (SS), resulting in the following function:

$$P = f(MIV, TI, \frac{T}{B}, SFP, OE, SS)$$

Where TI, T/B, SFP, OE, and SS were categorical variables.

The ANNs were trained and validated in Neuro software version 4.0 (Binoti, 2012). The maximum-minimum normalisation (1) was applied to the data, generating the following formula:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \in [0,1] \tag{1}$$

Where

$X_{norm}$  = normalised data,

$X$  = a value data,

$X_{min}$  = minimum value data, and

$X_{max}$  = maximum value data

Sigmoid activation function (2) was applied to the hidden and output layers:

$$f(\alpha) = \frac{1}{(1 + e^{-\alpha})} \tag{2}$$

Where

$f$  = non-linear activation function used throughout the neural network

$b$  = bias for neuron activation thresholds

$x_i$  = input values

$w_i$  = corresponding weights of input values

$\alpha$  = weighted combination of these inputs and weights:

$$\alpha = \sum_{j=1}^m w_j x_j + b$$

The number of neurons in the hidden layer was expressed as a function of the number of input variables, which was obtained by averaging the number of continuous and categorical variables to produce a value of eight neurons. The stopping criteria achieved a mean error of 0.0001 and 3000 epochs (Casas et al., 2022a).

The Rprop algorithm (Riedmiller & Braun, 1993) was used, following the rule for each weight,  $\omega_{ij}$ , and individual step-size,  $\Delta_{ij}$ :

$$\Delta_{ij}^{(t)} = \begin{cases} \min(\eta^+ * \Delta_{ij}^{(t-1)}, \Delta_{max}), & \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0 \\ \max(\eta^- * \Delta_{ij}^{(t-1)}, \Delta_{min}), & \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0 \\ \Delta_{ij}^{(t-1)}, & \text{otherwise.} \end{cases}$$

The four variations of the Rprop algorithm (Rprop+, iRprop+, Rprop-, and iRprop-) were used in this study to train 50 models (Igel & Hüsken, 2003):

**Algorithm 1: Rprop+**

*Rprop+*  
 for each  $\omega_{ij}$  do {  
 if  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0$  then {  
 $\Delta_{ij}^{(t)} = \min(\Delta_{ij}^{(t-1)} * \eta^+, \Delta_{max})$   
 $\Delta \omega_{ij}^{(t)} = -\text{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)}$   
 $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$   
 }  
 elseif  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0$  then {  
 $\Delta_{ij}^{(t)} = \max(\Delta_{ij}^{(t-1)} * \eta^-, \Delta_{min})$   
 $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$   
 $\frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0$   
 }  
 elseif  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0$  then {  
 $\Delta \omega_{ij}^{(t)} = -\text{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)}$   
 $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$   
 }  
 }

**Algorithm 3: Rprop-**

*Rprop-*  
 for each  $\omega_{ij}$  do {  
 if  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0$  then {  
 $\Delta_{ij}^{(t)} = \min(\Delta_{ij}^{(t-1)} * \eta^+, \Delta_{max})$   
 }  
 elseif  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0$  then  
 $\Delta_{ij}^{(t)} = \max(\Delta_{ij}^{(t-1)} * \eta^-, \Delta_{min})$   
 }  
 $\Delta \omega_{ij}^{(t)} = -\text{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)}$   
 }

$0 < \eta^- < 1 < \eta^+$ , and the updated weights were given by  $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$ . If  $\partial E / \partial \omega_{ij}$  maintained the same sign, the step size increased; if the value changed, the step size decreased.

The data were handled using a computing setup running a 64-bit version of Windows 10 Professional. The device was equipped with an Intel Core i3 6006U processor clocked at 2.00 GHz built on 14nm Skylake-U/Y architecture, 12 GB of dual-channel RAM operating at 1064 MHz with

**Algorithm 2: iRprop+**

*iRprop+*  
 for each  $\omega_{ij}$  do {  
 if  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0$  then {  
 $\Delta_{ij}^{(t)} = \min(\Delta_{ij}^{(t-1)} * \eta^+, \Delta_{max})$   
 $\Delta \omega_{ij}^{(t)} = -\text{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)}$   
 $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$   
 }  
 elseif  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0$  then {  
 $\Delta_{ij}^{(t)} = \max(\Delta_{ij}^{(t-1)} * \eta^-, \Delta_{min})$   
 if  $E^{(t)} > E^{(t-1)}$  then  $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$   
 $\frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0$   
 }  
 elseif  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0$  then {  
 $\Delta \omega_{ij}^{(t)} = -\text{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)}$   
 $\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)}$   
 }  
 }

**Algorithm 4: iRprop-**

*iRprop-*  
 for each  $\omega_{ij}$  do {  
 if  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0$  then {  
 $\Delta_{ij}^{(t)} = \min(\Delta_{ij}^{(t-1)} * \eta^+, \Delta_{max})$   
 }  
 elseif  $\frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0$  then {  
 $\Delta_{ij}^{(t)} = \max(\Delta_{ij}^{(t-1)} * \eta^-, \Delta_{min})$   
 $\frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0$   
 }  
 $\Delta \omega_{ij}^{(t)} = -\text{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)}$   
 }

timing configuration of 15-15-15-35, a LENOVO motherboard identified as LNVNB161216 (U3E1), a standard PnP display with a 1366×768 resolution at 64 Hz, and a 465 GB solid-state drive connected via SATA, specifically the Western Digital model WDS500G2B0B-00YS70. On average, the training process for each neural network model spanned approximately five minutes to complete under these hardware conditions.

**2.3. Model performance**

The database was divided into two categories for training (70%) and validation (30%). The bias-variance trade-off was analysed for the training data. Subsequently, the models with the best statistical performance of the 50 trained models for each algorithm were selected for data validation.

The following statistical criteria are considered in the data validation step:

Linear correlation coefficient (3) between observed and estimated productivity ( $r_{y\hat{y}}$ ):

$$r_{y\hat{y}} = \frac{n^{-1} \sum_{i=1}^n (Y_{pi} - \hat{Y}_m)(Y_i - \bar{Y})}{\sqrt{n^{-1} \sum_{i=1}^n (Y_{pi} - \hat{Y}_m)^2 n^{-1} \sum_{i=1}^n (Y_i - \bar{Y})^2}};$$

$$\hat{Y}_m = n^{-1} \sum_{i=1}^n Y_{pi} \tag{3}$$

Square root of the mean square error (RMSE%) (4):

$$RMSE\% = 100 \bar{Y}_i^{-1} \sqrt{n^{-1} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2} \tag{4}$$

Percentage of relative error (ER%) (5):

$$ER\% = 100 \left( \frac{\hat{Y}_i - Y_i}{Y_i} \right) \tag{5}$$

Bias-variance trade-off (6) and (7) were used to determine the tendency of the measurement process,

$$Bias = 100 Y_i^{-1} \sum_{i=1}^n \left( \frac{\hat{Y}_i - Y_i}{n} \right) \tag{6}$$

$$VAR = \frac{\sum (bias - (\hat{Y}_i - Y_i))^2}{n-1} \tag{7}$$

Where

- n = number of observations,
- $Y_i$  = observed productivity ( $m^3 \cdot h^{-1}$ ),
- $\hat{Y}_i$  = observed productivity ( $m^3 \cdot h^{-1}$ )
- $\bar{Y}_i$  = mean observed productivity

### 3. RESULT AND DISCUSSION

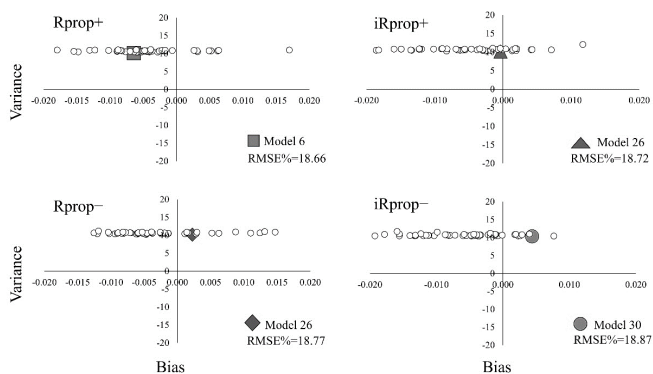
#### 3.1. Results

##### 3.1.1. Analysis of Rprop variants

The Rprop+ had a variation of  $21.259 \leq RMSE\% \leq 18.663$  with an average of 19.262 and a correlation variation of  $0.845 \leq r \leq 0.793$  with an average of 0.834, while the Rprop- had a variation of  $19.962 \leq RMSE\% \leq 18.768$  with an average of 19.171 and a correlation variation of  $0.843 \leq r \leq 0.820$  with an average of 0.835. In the case of iRprop+, a variation of  $28.257 \leq RMSE\% \leq 18.721$  with an average of 19.387 and a correlation variation of  $0.844 \leq r \leq 0.588$  with an average of 0.830, while iRprop- had a variation of  $20.087 \leq RMSE\% \leq 18.872$  with an average of 19.207 and a correlation variation of  $0.841 \leq r \leq 0.818$  with an average of 0.835.

In addition to the RMSE% statistical indicator and the correlation between estimated and observed harvester productivity, bias-variance trade-off (Figure 3) analysis was performed to select models with the best statistical performances and perform the data validation for each variation of the Rprop algorithm.

According to Islam et al. (2009), all cases in the present study belong to the high bias-low variance and high bias-high variance quadrants. Meanwhile, data training using the most iRprop+ and iRprop- models was categorised as a low bias-high variance quadrant.



**Figure 3:** Relationship between bias and variance of models trained with the four varieties of the Rprop algorithm for the harvester productivity model.

The models trained with Rprop+ presented a variation of  $0.017 \leq bias\% \leq -0.041$  with an average of  $-0.006$  and a variance of  $13.097 \leq variance \leq 10.095$  with an average of 10.757. Model 6 demonstrated the best statistical performances with  $RMSE\% = 18.66$ ,  $bias\% = -0.006$ , and  $variance = 10.095$ . Rprop- presented a variation of  $0.015 \leq bias\% \leq -0.075$  with an average of  $-0.005$  and a variance variation of  $11.544 \leq variance \leq 10.209$  with an average of 10.653. Model 26 recorded the best statistical performances

with  $RMSE\% = 18.77$ ,  $bias\% = 0.002$ , and  $variance = 10.209$ . iRprop+ presented a variation of  $0.024 \leq bias\% \leq -0.030$  with an average of  $-0.005$  and a variance variation of  $23.142 \leq variance \leq 10.158$  with an average of 10.941. Model 26 had the best statistical performances with  $RMSE\% = 18.72$ ,  $bias\% = 0.001$ , and  $variance = 10.158$ . iRprop- presented a variation of  $0.008 \leq bias\% \leq -0.019$  with an average of  $-0.006$  and a variance variation of  $11.693 \leq variance \leq 10.322$  with an average of 10.694. Model 30 demonstrated the best statistical performances with  $RMSE\% = 18.87$ ,  $bias\% = 0.004$ , and  $variance = 10.322$ .

##### 3.1.2. Best model comparison on data validation

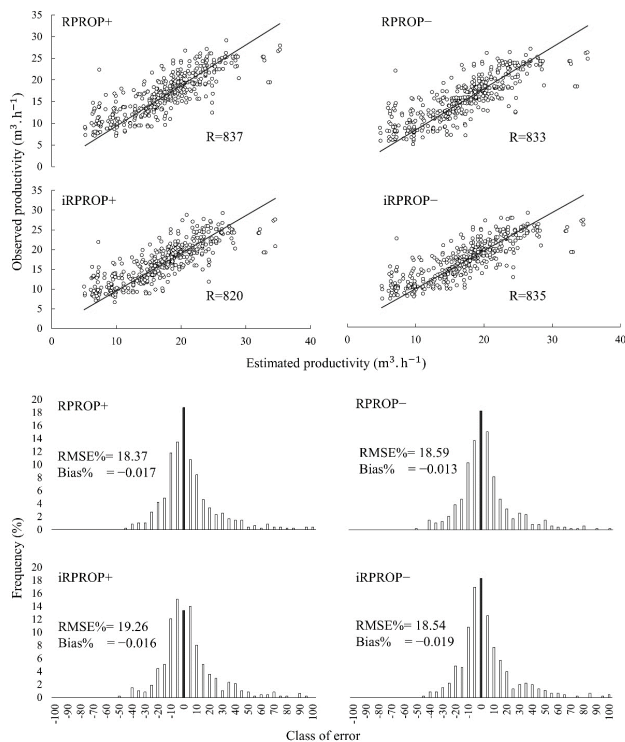
The models with the best statistical performance of each variation of the Rprop algorithm were used in the data validation stage (Table 3). The Rprop+ presented a statistical performance of  $r = 0.837$ ,  $RMSE\% = 18.380$ ,  $bias\% = -0.017$ , and  $variance = 9.867$ . The Rprop- recorded a statistical performance of  $r = 0.833$ ,  $RMSE\% = 18.590$ ,  $bias\% = -0.013$ , and  $variance = 10.125$ . The iRprop+ demonstrated a statistical performance of  $r = 0.820$ ,  $RMSE\% = 19.263$ ,  $bias\% = -0.016$  and  $variance = 10.848$ . The iRprop- presented a statistical performance of  $r = 0.835$ ,  $RMSE\% = 18.542$ ,  $bias\% = -0.019$ , and  $variance = 10.125$ .

**Table 3:** Statistical performance in the data validation stage for each Rprop algorithm to model harvester productivity.

Algorithm	$r_{y\hat{y}}$	RMSE (%)	Bias (%)	Variance
Rprop+	0.837	18.380	-0.017	9.867
Rprop-	0.833	18.590	-0.013	10.125
iRprop+	0.820	19.263	-0.016	10.848
iRprop-	0.835	18.542	-0.019	10.015

As the models presented similar correlation coefficient values, no differences were observed in the correlation graphs between estimated and observed productivity. Nonetheless, differences were evident when distributing the relative error by classes in relation to frequency (%) (Figure 4). Rprop+, Rprop-, and iRprop- followed normality principles, and most data were classified as zero error. Rprop+ recorded the highest percentage in that class. According to the criteria analysed, the Rprop+ algorithm yielded the best statistical performance among other algorithm variations.

The L&O identity test (Leite & Tavares de Oliveira, 2002) was used to verify whether the RPROP algorithm variants produce statistically equivalent results in modelling forestry harvester productivity.



**Figure 4:** Correlation plot between estimated and observed productivity (top) and error class plot between frequency (%) (bottom) for the harvester productivity model.

This test integrates bias, regression conformity, and correlation; thus, suitable for evaluating analytical agreement in forestry data such as plantation productivity metrics. The Rprop+ was set as the reference method for this purpose. None of the other variants (iRprop+, iRprop-, Rprop-) met the identity criteria, indicating that the results were statistically different. Thus, Rprop+ demonstrated superior and distinguishable performance among the tested algorithms.

### 3.2. Discussion

Harvester productivity is affected by numerous variables. Malinovski et al. (2006) identified 35 that covered physical characteristics of the land, stands, and forest operational planning. Thus, this study aimed to narrow down key variables that are practical, easily detected, confirmed by experts in tractor manipulation, and in coherence with the scientific knowledge proven by earlier studies. Operator experience is one of the crucial variables in determining machine productivity for wood cutting (Lopes et al., 2022). Highly experienced and skilled operators often determine the ergonomic outcomes that affect the forest harvesting activities (Schettino et al., 2022). In addition, a meta-analysis conducted on manual tree felling activities across five continents revealed that tree diameter (DBH), distance to trees, stand density, and slope were primary factors affecting productivity (Ghaffariyan, 2021), reflecting the importance of planning and sizing of forest harvesting activities (Malinovski et al., 2006). Tree characteristics were another variable that

directly affected productivity due to the strong link to harvester tree felling and limbing operation (Rodrigues et al., 2018).

In this study, four variants of the Rprop algorithm were applied to estimate the harvester productivity, utilising key variables in the harvesting process. The Rprop+ used in this study refers to the original algorithm proposed by Riedmiller and Braun (1993), which demonstrated superior statistical performance compared to other variations. This algorithm is often used to solve forestry modelling problems for eucalyptus plantations in Brazil, yielding satisfactory results in forest harvesting. Lacerda et al. (2022) also reported using the Rprop algorithm with the ANN technique to estimate the mechanical availability of forest harvesting equipment, presenting a high statistical performance. The Rprop was also useful in estimating specific fuel consumption of the harvester based on climatic, dendrometric, and operational factors (Santos, 2018). An earlier study also utilised the Rprop algorithm to estimate harvester productivity using forest variables (age, average individual tree volume, and tree density), machine (machine code at the company) and planning (harvest bimonthly, equipment and grading), obtaining an RMSE% = 18 for the training data and RMSE% = 20 for the validation data (Friederichs, 2016). These outcomes were comparable with the results obtained in the current study.

Previous studies have indicated that model correlation can vary widely depending on data conditions and modelling scope. In the current context, differences in variable selection criteria and algorithm choice contribute to variability in the performance of harvester productivity estimates. Input variables, such as average tree volume, stand timber volume, cutting age, spacing, operator experience, and management regime, have been used in various machine learning approaches to model harvesting productivity, with reported correlation coefficients beyond 0.9. (Gonçalves et al., 2021). Meanwhile, using various algorithms in the default mode (set-mixing, set-stacking) and algorithmic learning methods for harvester productivity estimation yielded a coefficient of determination ( $R^2$ ) of 0.71 (Munis et al., 2022). These findings were comparable with the current results, indicating that an  $r < 0.80$  is typical when modelling productivity across diverse operational conditions.

The literature highlighted that differences in operator performance contribute to significant variability in productivity (20–40%). Meanwhile, operator proficiency explained 37% to 40% of the variance in cycle times. Additionally, terrain and site factors, including terrain slope, ground conditions, and site layout, impact harvester productivity. Steeper slopes or soft

soil diminish work rates compared to gentle terrain. Variation in terrain classes and undergrowth conditions requires explicit features for accurate modelling (Schwegman et al., 2023). Tree form and stand conditions, including forks, large limbs, and crooked stems, can also reduce harvester efficiency by 15% to 20%. Moreover, variability in eucalyptus clones or growth conditions may introduce unexplained variance (Labelle et al., 2016).

The Rprop+ algorithm used in this study includes a weight-backtracking mechanism. When the gradient sign changes to indicate a possible overshoot of a minimum, the algorithm partially reverses the last weight update. This change prevents oscillations and costly errors, enhancing convergence reliability. Studies have demonstrated that Rprop variants with weight-backtracking (Rprop+ and iRprop+) consistently outperform algorithms without this feature (Rprop-, iRprop-) in achieving fast results with fewer errors. Thus, improved Rprop algorithms such as iRprop+ have been recommended for robust first-order training on large neural networks. The performance differences between Rprop+ and iRprop+ are often minor, which aligns with observations that the original Rprop+ achieved results as good as, or better than, the improved variants for the given dataset (Igel & Hüsken, 2003). The weight-backtracking in Rprop+ provided stability and prevented adverse local minima, yielding a consistent convergence path. Simplicity, immunity to poor learning-rate choices, and fast gradient adaptation are other Rprop features that contribute to effective modelling of the complex, sensor-derived forestry data (Chen & Lin, 2011).

Should real-time or large-scale deployment be considered, the Rprop+ training approach presents clear advantages that may be adapted and expanded upon in future research. This algorithm is computationally efficient without requiring second-order matrices or large batch computations. As the model size or dataset expands, the training process remains manageable on standard hardware. In the present study, the network for harvester productivity is relatively small, and Rprop converged successfully in a few hundred iterations.

The current study has several limitations. Firstly, the estimation of harvester productivity is complex due to the influence of various factors and characteristics, despite obtaining statistical gain using neural network methods. Secondly, periodic calibration of the sensors is necessary to produce accurate results, as quantitative data are obtained from sensors and input into the harvesting head (Tao & Qi, 2019).

## 4. CONCLUSION

This study assessed four variants of the Rprop algorithm to estimate harvester productivity based on categorical and quantitative field variables. Among the tested models, Rprop+ yielded the best statistical performance on the validation dataset (RMSE% = 18.380, bias% = -0.017, variance = 9.867) and was statistically superior according to the L&O identity test. The overall performance among variants was similar, with Rprop+ consistently demonstrating greater predictive reliability. As the dataset was obtained from onboard harvester sensors, the methodology benefits from operational data. Future research can utilise this advantage by exploring real-time modelling approaches and deploying adaptive neural network models capable of responding dynamically to field conditions.

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