A NEURAL NETWORK MODEL FOR WOOD CHIP THICKNESS DISTRIBUTIONS

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ABSTRACT

Wood chip thickness is an important factor in pulp quality and yield. An artificial neural network model was developed and incorporated into a growth and yield simulator to predict wood chip thickness distributions from stand and tree characteristics. Models based on direct parameter estimation and parameter recovery were also developed for comparison to the neural network. Data were derived from 11,771 individual loblolly pine chip thickness measurements. Four stand ages, five dbh (diameter at breast height) classes, and three stem positions were used to predict the cumulative proportion of chip weight per chip thickness class. Results showed that the neural network model was superior to the two deterministic models on the basis of bias, root mean square error, and index of fit. Sensitivity analyses for the neural network model demonstrated that thicker chips were produced by younger stands and lower stem positions. The neural network was combined with a growth and yield simulator to demonstrate its use as a tool for procurement foresters and mill managers in predicting yields from stands of given characteristics.

Keywords: Neural network, wood chips, wood chip thickness, wood chip thickness distributions.

INTRODUCTION

Wood chip thickness is a major factor in the performance of pulp digesters and in subsequent pulp quality and yield (Borlew and Miller 1970; Becker 1992; Tikka et al. 1993). Different pulping methods require different chip thicknesses (Dubois et al. 1991; Wood and Gosda 1992). Chip thickness below or above an optimum range produce either overcooked or undercooked pulp, thereby reducing process and fiber efficiencies (Worster et al. 1977; Christie 1987). The control of chip thickness distributions readily translates into increased yield per unit cost and has been studied from four different approaches or production phases: 1) prechipping wood conditions (Flowers et al. 1992; Wallace et al. 1992; Koger et al. 1993); 2) mechanical considerations during chipping (Twaddle and Watson 1990; Dubois et al. 1991; Uelmen 1993); 3) screening of chips prior to pulping (Christie 1987;

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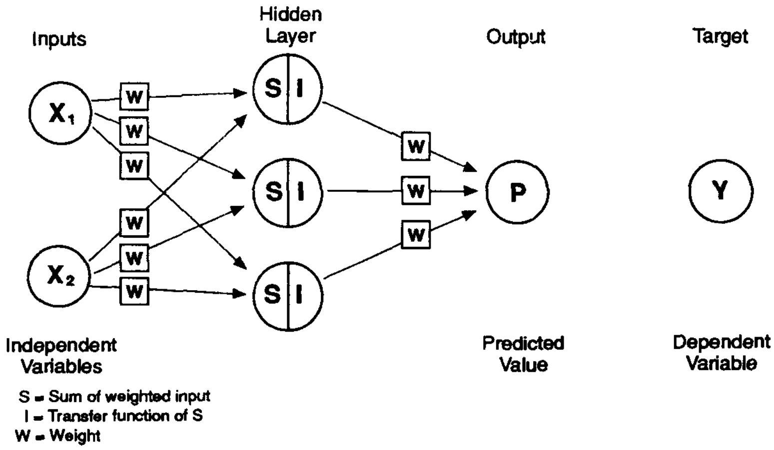

FIG. 1. A simple multilayer neural network.

Tikka et al. 1993); and 4) pulping conditions (Worster et al. 1977; Becker 1992).

Prediction of chip thickness distributions from prechipping wood conditions has several advantages. It can change the magnitude or type of control needed in later production phases, and it allows the purchase price of roundwood to be based on projected yields. Prechipping studies by Flowers et al. (1992) and Koger et al. (1993) showed that stand age, dbh (diameter at breast height) class, and chip position in the stem influenced the distribution of chip weights by thickness class. Given adequate prediction equations, these variables could be readily manipulated to increase pulp yields.

The objective of our study was the enhancement of modeling techniques for predicting chip thickness distributions from prechipping stand and tree characteristics. We developed and compared three models. The best model was integrated with a growth and yield simulator for the purpose of predicting total chip weight by thickness class for stands of a given age, site index, and merchandizing standards. The utility of the integrated model for the procurement forester and mill manager is twofold: 1) the prediction of chip yields from stands under consideration for purchase or scheduled for harvest; and 2) the prediction of yields from the manipulation of management, harvesting, and chipping strategies. The objective of manipulating chipping strategies could be either optimum chip thickness or optimum chip thickness mixes.

MODELING APPROACHES

We selected two parametric methods and one nonparametric method for predicting chip thickness distributions. The parametric methods, based on the Weibull distribution function, were direct parameter prediction and parameter recovery. The nonparametric approach was a neural network. Each approach and its advantages are discussed below. Bias, precision, and index of fit statistics were used to compare the three models and to select the best one for integration with the growth and yield simulator.

Neural networks

The use of neural networks, formally called *artificial neural networks,* is a technique from the field of artificial intelligence that attempts to simulate human cognitive behavior. There are numerous neural network types, but perhaps the most popular is the back-propagation network. A multilayered, back-propagation network (Fig. 1) is composed of an input layer, an output layer, and one or more middle layers called hidden layers. Each layer contains a number of nodes that hold and transmit calculated values. The input layer contains one node for each independent variable in the model, and the output layer contains one node for each dependent variable in the model. Trial and error testing during network construction determines the number of hidden layers and number of nodes per hidden layer. Values travel in one direction along connecting links, from nodes in the input layer to nodes in the output layer. Each link is associated with an iteratively calculated weight.

There are two phases of network development, a training phase and a testing phase. Learning (weight adjustment) and model building occur in the training phase. Evaluation of models occurs in the testing phase. During training, the nodes of the input layer receive scaled data values from the independent variables. Each input node value is multiplied by the corresponding weights of its links, and the products are transmitted to connecting nodes in the first hidden layer. The weighted values from each input node are summed, transformed by a smoothing or transfer function, and stored in a hidden layer node. The weighting, summation, and transformation process is repeated from layer to layer until the output layer is reached. Node values are descaled at the output layer.

The difference between the output node values (predicted output) and their paired target values (observed output) is used to adjust the network weights by propagating errors back through the network according to a learning rule. Weights are adjusted in proportion to the product of a learning rate, an error derivative, and the output from the previous layer (NeuralWare 1993; Weiss and Kulikowski 1991). The neural network produces a nonlinear model whose parameters, the network weights, are adjusted after each input or epoch (specified number of inputs).

During the testing phase, values travel through the network in the same manner as in the training phase, except there is no updating of weights. Network inputs either come from random subsets of the training data or from an independent data set. As predicted output values are produced, they are compared to corresponding observed outputs to calculate a collective error. The best of many models is usually chosen on the basis of the lowest root mean square error.

There are several general advantages of neural networks as compared to traditional modeling techniques. Neural networks assume no predetermined functional form, and thus no prior knowledge of the model is needed. They are particularly well adapted to applications where no suitable mathematical model is known or where systems may be composed of complicated interactions.

A noted disadvantage of neural networks is the inability to place logical constraints on the output. Another disadvantage can be the magnitude of data needed during the training phase. Problems that produce small data sets are not well suited to modeling with neural networks.

Direct parameter prediction

The direct parameter prediction approach involves identifying a parametric probability function that closely approximates the observed distribution. The parameters of the selected distribution are estimated by maximum likelihood estimation or by non-linear least squares fittings of the cumulative distribution function to the empirical distribution functions. Parameter estimates are then regressed on the predictor variables to build a distribution prediction model (Bailey and Dell 1973; Dell et al. 1981; Kendal and Stuart 1977).

Parameter recovery

The parameter recovery method for estimating parametric distributions is an indirect technique. First, regression equations are found for predicting selected moments (mean or quadratic mean) and/or order statistics from the predictor variables associated with each distribution. The expected value equation derived for each predicted moment or order statistic is equated to its corresponding regression equation, and the subsequent linear/nonlinear system of equations is then solved for the desired parameter estimates (Farrar and Matney 1994; Kendal and Stuart 1977; Matney and Farrar 1992; Matney and Sullivan 1982a, b; Zarnoch et al. 1991).

Unlike the neural network, both parametric approaches are bound to a particular functional form and automatically impose logical constraints. These approaches can yield excellent predictions if the assumed distribution closely approximates the actual distribution. On the other hand, when the actual distribution is complex, multi-modal, or discontinuous, these approaches are of limited value.

DATA

The data consisted of measurements taken on 11,771 individual loblolly pine wood chips. Green Bay Packaging Company's plantations near Morrilton, Arkansas, supplied the trees. Three to ten trees were selected from within each of four stand ages (14, 19, 23, and 29 years) and five diameter classes (5, 7, 9, 11, and 13 inches dbh). Debarked tree length stems were individually identified and chipped in diameter-age groups. Price Industries in Perry, Arkansas, chipped the trees. Chip samples were taken from the butt (1), middle (2), and top (3) thirds of each group of stems. Details on the chipper set-up are found in a previous study by Koger et al. (1993). Chips were classified with a Gradex classifier to determine the percentage of fines, pins, accepts, and overs. Individual chip thickness measurements were made with an electronic caliper, and each chip was weighed to the nearest hundredth of a gram. Chips that were less than 2 millimeters in thickness were not individually measured but were collectively weighted by stand age-diameter-stem position class. The average chip thickness was 3.88 millimeters, and the average chip weight was 0.56 grams (Koger et al. 1993).

The independent variables for the three models were stand age, dbh class, chip position in the stem, and chip thickness. There were a total of 54 bulk samples representing unique combinations of variable levels. The dependent variable was defined as the cumulative proportion of chip weight that is less than or equal to each unique chip thickness. The cumulative proportion, though not a relative frequency probability distribution, does share the same properties of probability distributions, and these properties were important in the development of the parametric approaches. Instead of predicting the relative numbers of chips of a specified thickness, the models predict the cumulative proportion of the total weight of chips having a specified thickness.

METHODS

Neural network

We used NeuralWare's Neural Works Professional II/Plus (NeuralWare, Inc., Pittsburgh, PA) software to construct the neural network model. The software ran on a SUN 690 MP minicomputer. Many network types are available through the NeuralWorks software, but we selected the commonly used fully connected, hetero-associative, feed forward, back-propagation form. Feed forward networks (like the back-propagation learning system) have been mathematically proven to be capable of approximating continuous functions to any degree of accuracy (Hassoun 1995).

Building a back-propagation network with NeuralWorks requires the selection of various parameters. We based some parameter selections on NeuralWare's recommendation and others on trial and error experimentation and minimum root mean square error. Table 1 summarizes the selected parameters. Different values of the parameters in Table 1 constitute separate networks that were tested. We tried network architectures with one, two, and three hidden layers and with a varying number of nodes per layer. An architecture of two hidden layers with eight nodes in the first hidden layer and four nodes in the second hidden layer was chosen because it produced the least root mean square error of the models tested.

TABLE 1. *Selected NeuralWorks Professional II/Plus network parameters.*

Parameter	Value	Description
Network type	back-propagation	back-propagation of errors
	hetero-associative	different input and output variables
	min-max table	scaled inputs
	fully connected	all nodes connected in adjacent layers
Learning rule	delta rule	governs weight adjustments
Transfer function	sigmoid	smoothing function
Epoch size	1 = standard for delta rule	no. inputs per weight update
No. hidden layers (HL)	2	
No. nodes/hidden layer	HL1 = 8, HL2 = 4	
Momentum	0.8	modifies weights to deter convergent behavior
Learn counts (in thousands)	HL1 = 10, 30, 70, 150, 310 HL2 = 10, 30, 70, 150, 310 Output = 10, 30, 70, 150, 310	the sequential number of inputs for which a learning coefficient applies
Learning coefficients	HL1: 0.9, 0.45, 0.225, 0.1125, 0.00001 HL2: 0.6, 0.3, 0.15, 0.07, 0.00001 Output: 0.15, 0.075, 0.01875, 0.00117, 0.00	multipliers in the calculation of weights; values change after a set number of inputs (learn count)

A network stopping criterion of 300,000 network cycles was determined during preliminary testing. One chip observation is processed by one network cycle. During preliminary tests, the neural networks were allowed to run with no stopping criterion until improvements in error were no longer made. This always occurred before 300,000 network cycles.

NeuralWorks randomly presented samples of the chip measurements to the networks for training. Sampling occurred without replacement until all 11,771 observations were presented at least once. Random sequences of the 11,771 observations were presented repeatedly until the stopping criterion was reached. Sample sizes consisted of approximately 17% of the chip measurements. Different sample sizes were tested, but those larger than 17% showed no improvement in root mean square error.

One hundred and forty-eight models were generated for each network architecture. The model with the least root mean square error (Fig. 2) was selected and output through a NeuralWorks utility in standard C language source code. Bias, root mean square error (RMSE), and index of fit were calculated for comparison with the two parametric models (Table 2). Bias was calculated as the average difference between observed and predicted values, and index of fit was calculated as one minus the quantity of the error sum of squares divided by the total sum of squares.

Direct parameter prediction

Previous work by Koger (1994) demonstrated that extremely close approximations to the normalized weighted chip distributions could be obtained by nonlinear least squares fitting of the cumulative distribution of a three-parameter Weibull function. The Weibull cumulative distribution function was thus accepted as the appropriate model for predicting cumulative chip weight distributions. The Weibull distribution can assume many shapes, and because of this flexibility has been widely applied in forestry and other fields to model distributions. The following cumulative Weibull distribution function equation was employed in an SAS (SAS Institute Inc., Cary, NC) Guass-Newton *NONLIN* procedure to produce parameter estimates.

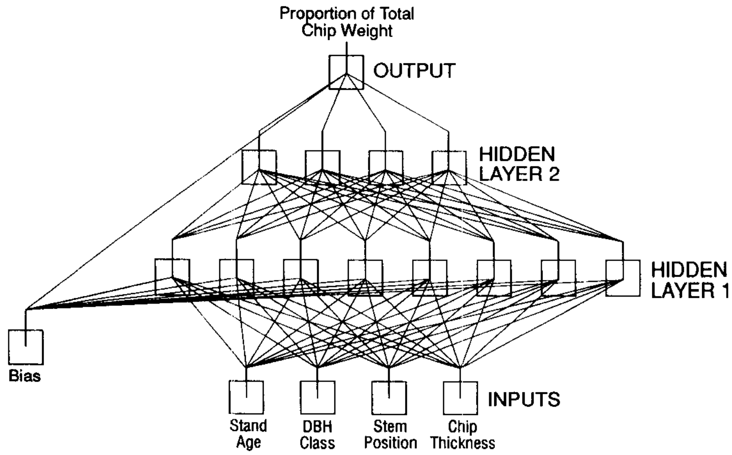

FIG. 2. Neural network architecture that possessed the least root mean square error.

$$F(t) = 1 - e^{-|(t-a)/b|^c} \quad (1)$$

where

F(t) = weight proportion of chips less than or equal to a thickness of t,

t = chip thickness in millimeters,

a = location parameter (the minimum chip thickness),

b = scale parameter,

c = shape parameter, and

e = base of the natural (Naperian) logarithm.

All a parameter estimates obtained the logical lower bound of 0. As a result, we elected to use the following two-parameter Weibull equation for both the direct and recovery modeling approaches.

$$F(t) = 1 - e^{|t/b|^c} \quad (2)$$

After estimates of the b and c parameters were obtained, a regression analysis was performed to find the *best* equations to predict the model parameters from the 54 combinations of stand age (age), tree dbh class (dbh), and stem position (pos). The best parameter prediction equations developed were:

TABLE 2. *Bias, root mean square error, and index of fit by chip thickness class for the three modeling approaches.*

Chip thickness class (mm)	No. obs.	Neural network		Parameter recovery		Direct parameter	
		Bias	RMSE	Bias	RMSE	Bias	RMSE
0	8	0.002	0.004	−0.001	0.007	0.002	0.004
1	389	−0.001	0.011	−0.032	0.037	−0.012	0.015
2	3,184	−0.002	0.026	−0.043	0.052	−0.003	0.030
3	3,039	0.005	0.056	−0.010	0.060	0.024	0.069
4	2,393	0.000	0.072	0.038	0.088	0.030	0.088
5	1,467	0.000	0.077	0.064	0.108	0.008	0.089
6	688	−0.009	0.071	0.042	0.088	−0.038	0.087
7	356	−0.005	0.063	0.012	0.069	−0.062	0.091
8	160	−0.004	0.057	−0.013	0.063	−0.061	0.085
9	47	−0.002	0.042	−0.023	0.049	−0.050	0.065
10	40	0.000	0.000	0.014	0.016	0.001	0.002
All	11,771	0.000	0.057	0.003	0.073	0.007	0.070
Index of Fit		0.957		0.929		0.936	

$$b = 7.6995 - 0.05557\text{age} + 0.06935\text{dbh} - 1.5047\text{pos} + 0.2909\text{pos}^2 \quad (3)$$

$$s_{y.x} = 0.56, \quad r^2 = 0.41$$

$$c = 3.4975 \quad (4)$$

$$s_{y.x} = 0.75, \quad r^2 = 0.0$$

The shape parameter, c, was not related to the independent variables; thus the best estimate of this parameter was the average value. The scale parameter, b, was strongly associated with the independent variables, indicating that the primary effect of age, dbh, and stem position was on the spread (variance) of chip distributions. A two-parameter Weibull distribution has variance

$$\sigma^2 = b^2(\Gamma(1 + 2/c) - \Gamma(1 + 1/c)^2) \quad (5)$$

where

$\Gamma(\alpha)$ = the value of the gamma function with argument α.

With the *c* parameter fixed, the variance is directly proportional to b^2.

Parameter recovery

The parameter recovery approach was also based on the two-parameter Weibull distribution function. In this approach, equations were derived for estimating the first and second order moments (arithmetic and quadratic means) of the two-parameter Weibull.

$$E(t) = \bar{t}_a = b\Gamma(1 + 1/c) \quad (6)$$

$$E(t^2) = \bar{t}_q^2 = b^2\Gamma(1 + 2/c) \quad (7)$$

where

$E(t) = \bar{t}_a$, the expected value of t (first order moment),

$E(t^2) = \bar{t}_q^2$, the expected value of t^2 (second order moment), and

$\Gamma(\alpha)$ = the value of the gamma function with argument α.

Equations for estimating $\bar{t}_a$, and $\bar{t}_q$ were derived from the data and equated to their expected values. The resulting set of nonlinear simultaneous equations were solved for the unknown parameters b and c using the following four steps.

1. The first moment expected value equation was solved for b in terms of $\bar{t}_a$ and c.

$$b = \frac{\bar{t}_a}{\Gamma(1 + 1/c)} \quad (8)$$

2. The b parameter of the second moment expected value equation was replaced with the right-hand side of the derived equation in step 1 to obtain an equation involving only the parameter c and the estimated (known) values for $\bar{t}_a$ and $\bar{t}_q$.

$$\bar{t}_q^2 = \left(\frac{\bar{t}_a}{\Gamma(1 + 1/c)}\right)^2 \Gamma(1 + 2/c) \quad (9)$$

3. The equation obtained in step 2 was solved for the c parameter using bisection, a nonlinear equation solution algorithm (Burden et al. 1981).
4. The b parameter value was calculated from the equation in step 1 using the value for the c parameter found in step 3.

Equations for predicting $\bar{t}_a$, and $\bar{t}_q$ were obtained by calculating estimates of $\bar{t}_a$, and $\bar{t}_q$ for each of the 54 chip distributions representing different combinations of variable levels. These estimates were then regressed on stand age, dbh class, and stem position resulting in the prediction equations:

$$\bar{t}_a = 6.9960 - 0.04204\text{age} + 0.05721\ \text{dbh} - 1.2925\text{pos} + 0.2390\text{pos}^2 \quad (10)$$

$$s_{y.x} = 0.47, \quad r^2 = 0.43$$

$$\bar{t}_q = 7.3485 - 0.03822\text{age} + 0.06736\text{dbh} - 1.4995\text{pos} + 0.2988\text{pos}^2$$

$$s_{y.x} = 0.58, \quad r^2 = 0.32 \quad (11)$$

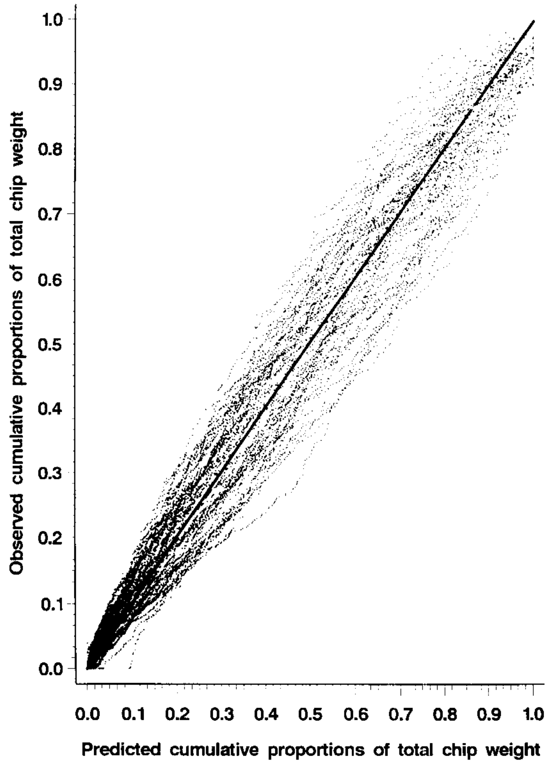

FIG. 3. The relationship between the observed and predicted chip thickness distribution functions for the neural network model.

The mean value equations applied to calculate empirical values of $\bar{t}_a$, and $\bar{t}_q$ for each distribution were:

$$\bar{t}_a = \frac{\sum_{i=1}^{i=n} w_i t_i}{\sum_{i=1}^{i=n} w_i} \quad (12)$$

$$\bar{t}_q = \sqrt{\frac{\sum_{i=1}^{i=n} w_i t_i^2}{\sum_{i=1}^{i=n} w_i}} \quad (13)$$

w_i = weight of chips with thickness t_i, and
n = number of chips in the sample bag.

The neural net based model and the two Weibull models of chip thickness distribution estimate the relative proportion of chip weight for a given chip thickness and not the relative frequency of chips by thickness. Chip thickness moments estimated from the distributions are chip weight weighted moments and not frequency weighted moments. Consequently, for the moment recovery procedure to produce estimated Weibull distributions with the required weighting, the above chip weight weighted average formulas must be used. For comparison purposes, the traditional frequency weighted mean chip thickness and root mean chip thickness are:

$$\bar{t}_a = \frac{\sum_{i=1}^{i=n} f_i t_i}{\sum_{i=1}^{i=n} f_i}, \quad (14)$$

and

$$\bar{t}_q = \sqrt{\frac{\sum_{i=1}^{i=n} f_i t_i^2}{\sum_{i=1}^{i=n} f_i}} \quad (15)$$

where

f_i = the frequency of chips in the sample with thickness t_i.

RESULTS AND DISCUSSION

The neural network model was selected as the best of the three models on the basis of bias, root mean square error (RMSE), and index of fit. Bias and RMSE were calculated by chip thickness category and as a composite over all thickness categories (Table 2). Calculating bias by thickness category typically reveals any tendency for a model to fit one class of thicknesses better than others. Results in Table 2 show that all models performed well in simulating the distribution of chip weights by thickness. However, the neural network gave the best results with an overall bias of zero, lowest RMSE, and highest index of fit. The direct prediction and parameter recovery methods produced some relatively large individual biases (−0.062 and 0.064, respec-

TABLE 3. *Bias and root mean square error by stand age for the three modeling approaches.*

Age class	No. obs.	Neural network		Parameter recovery		Direct parameter	
		Bias	RMSE	Bias	RMSE	Bias	RMSE
14	2,733	0.002	0.048	−0.010	0.058	−0.008	0.061
19	2,566	−0.010	0.050	0.010	0.070	0.014	0.060
23	3,218	0.007	0.066	0.028	0.088	0.036	0.082
29	3,254	−0.002	0.060	−0.016	0.071	−0.014	0.071
All	11,771	0.000	0.057	0.003	0.073	0.007	0.070

tively) compared to a maximum bias of 0.009 for the neural network. In general, direct prediction performed less well in the 6 to 9 millimeter range than in the other thicknesses, and parameter recovery performed less well in the 1 to 6 millimeter range. Bias was so low across thicknesses for the neural network that trends were not definitive. Index of fit was 2 to 3% better for the neural network than the other models. The relationship of the predicted and observed chip thickness distributions for the neural network is plotted in Fig. 3. Analyses were also conducted by individual variables of stand age, dbh class, and stem position (Tables 3–5). By-variable performance revealed no large divergent behavior for any of the models; however, bias appears to be less variable for all models by stem position.

The relationships among the independent variables of the neural network were defined by sensitivity analyses. Distributions of various combinations of stand age, dbh class, and stem position were determined by holding two variables constant while letting the third vary. Representative graphs of the chip thickness distributions in Figs. 4–6 depict the sensitivity of the network model to changes in the levels of the independent variables.

Of the three variables, stand age had the most dramatic effect on chip thickness. Figure 4 reveals that younger stands produced thicker chips. A comparison of chips from the same aged tree and stem position but varying in dbh class is shown in Fig. 5. The chip thickness distribution for the smallest (5-in.) dbh class was more narrow than those for the 9- and 13-in. dbh classes. The two larger dbh classes are skewed to the right in the thicker chip region. Figure 6 represents a comparison of chips from the same aged trees and the same dbh class but from varying tree positions. Chips from the lower third (butt) of the trees produced thicker chips than those from middle or top thirds.

Work by Koger (1994), Twaddle (1996), and others has described various underlying causal factors, like differences in wood properties and the mechanics of chipping, influencing the distributional patterns of chip thickness; but they suggest that the relationships of the factors are complicated and require further study. The causal relationships may not be clearly understood, but their effect in changing chip thickness by as little as 1 mm can have a major impact on pulp quality and pulping efficiency. The differences in distributions

TABLE 4. *Bias and root mean square error by dbh class for the three modeling approaches.*

Dbh class	No. obs.	Neural network		Parameter recovery		Direct parameter	
		Bias	RMSE	Bias	RMSE	Bias	RMSE
5	2,550	−0.006	0.054	0.001	0.071	−0.007	0.053
7	2,481	0.007	0.059	0.011	0.074	0.013	0.078
9	2,679	0.002	0.051	0.004	0.076	0.009	0.065
11	2,712	−0.009	0.064	−0.011	0.073	−0.002	0.075
13	2,393	0.011	0.057	0.017	0.075	0.035	0.080
All	11,771	0.000	0.057	0.003	0.073	0.007	0.070

TABLE 5. *Bias and root mean square error by stem position for the three modeling approaches.*

Tree stem pos. class	No. obs.	Neural network		Parameter recovery		Direct parameter	
		Bias	RMSE	Bias	RMSE	Bias	RMSE
1 = butt	3,169	−0.001	0.065	0.005	0.077	−0.001	0.074
2 = mid	4,198	0.001	0.055	0.005	0.074	−0.003	0.067
3 = top	4,404	−0.001	0.053	0.000	0.070	0.022	0.070
All	11,771	0.000	0.057	0.003	0.073	0.007	0.070

among variable levels, revealed in the sensitivity analyses, represent opportunities for the manipulation of chip thickness even though the underlying causal relationships are still undefined. Age and dbh are characteristics that can be readily manipulated by silvicultural treatments. Stem position might be manipulated during harvesting or chipping operations to optimize chip mixes.

APPLICATION

The ability to predict chip thickness distributions based on tree and stand characteristics could be used by procurement foresters and mill managers to estimate pulp yields from stands with given characteristics. To demonstrate this application, the neural network model was combined with a growth and yield model (Matney and Farrar 1992) so that site index, spacing, and merchandizing specifica-

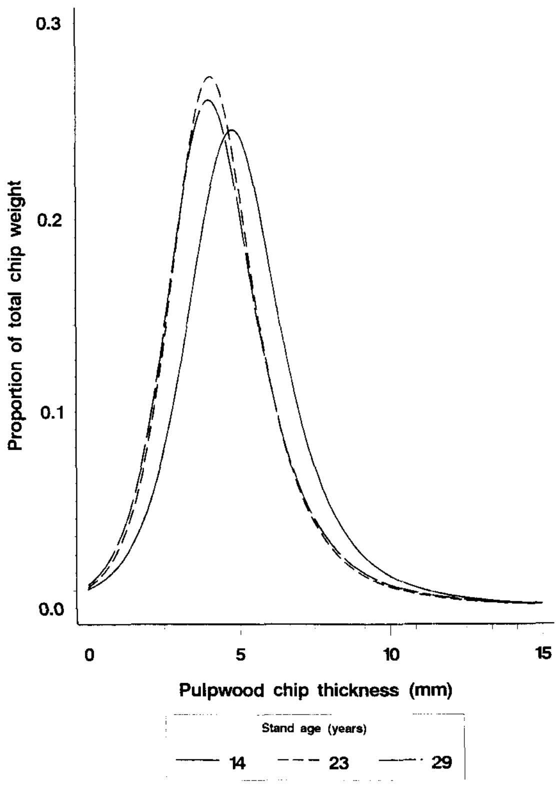

FIG. 4. Sensitivity of neural network estimated chip thickness distributions to age change, holding dbh and stem position fixed at 9 in. and middle position, respectively.

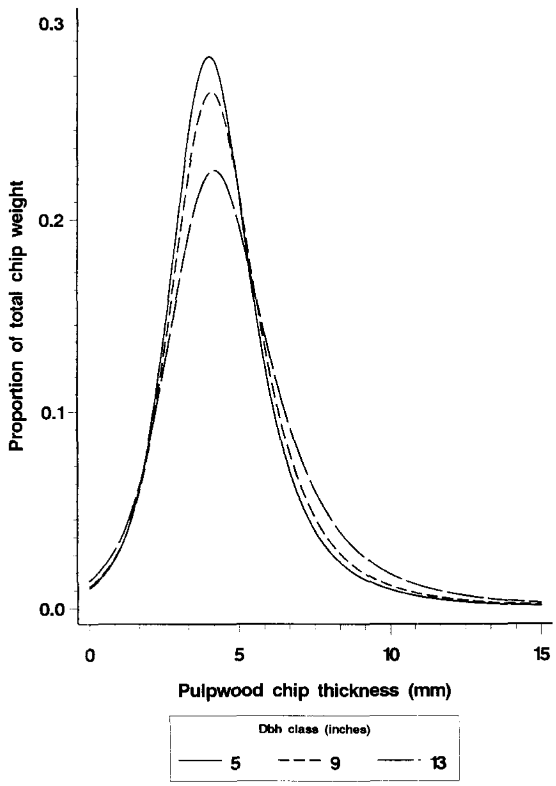

FIG. 5. Sensitivity of neural network estimated chip thickness to dbh change, holding age and stem position fixed at 23 yr and middle position, respectively.

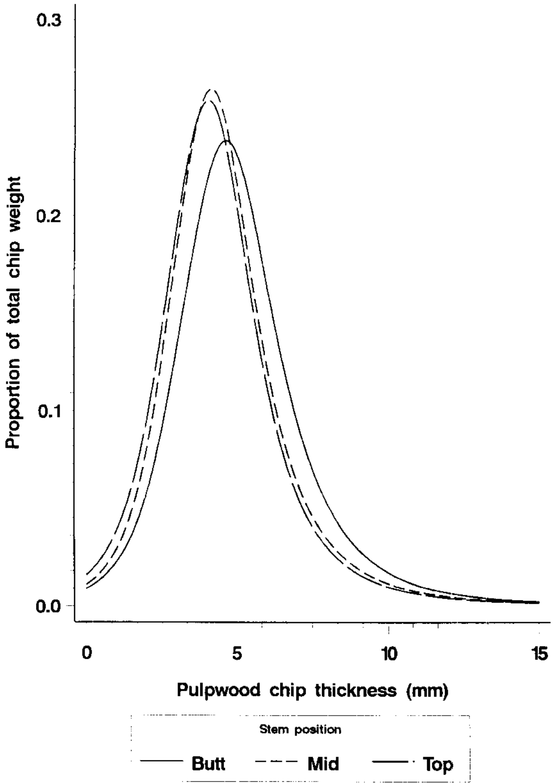

FIG. 6. Sensitivity of neural network estimated chip thickness distributions to stem position change, holding age and dbh fixed at 23 yr and 9 in., respectively.

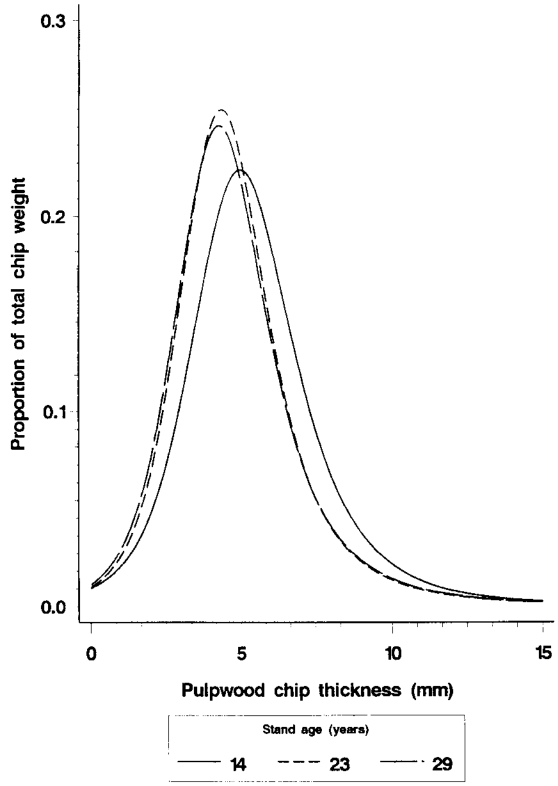

FIG. 7. Neural network estimated chip thickness distributions at ages 14, 23, and 29 for an unthinned loblolly pine plantation on site index (base age 25) 60 ft and having 450 surviving trees per acre at age 5 yr.

tions could be incorporated into yield estimates. The results of an example calculation are shown in Fig. 7. The selected stand has a site index of 60 ft (base age 25) and 450 trees per acre at age 5. Trees less than 10 in. in diameter (dbh) were considered pulpwood to a 3-in. diameter top. Trees greater than 10 in. in diameter were considered sawtimber to a 6-in. diameter top and pulpwood from 6 in. to a 3-in. diameter top. The growth and yield model was employed to calculate inside bark weights by stand age, dbh class, and stem position. The neural network model estimated the proportion of the chip weights falling into 15 thickness classes for each combination of variables. The proportion of each thickness class was multiplied by the total weight of chips to determine the total weight expected in each thickness class. Chip distributions for ages 14, 23, and 29 years are represented by separate curves in Fig. 7.

Supplied with this type of information, procurement foresters or mill managers could evaluate stands of trees according to their potential yields. Decisions could be made to harvest or leave stands to optimize current or future yields. The purchase price of wood could also be based on expected pulp yields.

The chip distributions reported here are applicable only to a specific set of stand and mill conditions; however, the neural network techniques could be easily adapted to any set of conditions and used to predict chip distributions for other mills.

CONCLUSIONS

Of the three approaches examined for modeling chip thickness distributions, the nonparametric neural network approach was superior. The network approach improved prediction over two good parametric methods and would be a preferred alternative to these more traditional approaches. Neural networks provide more flexibility in that models are not constrained to any predetermined functional form. They are also capable of modeling systems where no mathematical function is known or where complicated interactions may exist.

Sensitivity analyses for the neural network model showed that stand age has the greatest effect on chip thickness distributions. Thicker chips were produced by younger stands and lower stem positions. Larger dbh classes had slightly more variability in chip thickness. Additional studies need to be initiated to determine the cause of these distributional patterns.

The ability to predict chip thickness distributions with such low bias and high precision provides a powerful tool to the procurement forester and mill manager. They can predict what proportion of available chips will fall within the optimal thickness range for their pulping process. Combined with a growth and yield simulator, the neural network model can be used to value chips from stands according to their expected yields or manage and harvest stands in such a way as to increase yields.

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