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An artificial neural network for real-time hardwood lumber grading

Edward Thomas

Northern Research Station, USDA Forest Service, Princeton, WV, USA

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ABSTRACT

Computerized grading of hardwood lumber according to NHLA rules would permit fast assessment of sawn lumber and the evaluation of potential edging and trimming operations to improve lumber value. More importantly, to enable optimization of the hardwood lumber sawing process, a fast means of evaluating the potential value of boards before they are sawn is necessary. As log and lumber scanning systems become prevalent and common, these needs become more pressing. From an automation perspective, the NHLA lumber grades are difficult to implement efficiently in a computer program. Exhaustive approaches that examine every potential cutting size and combination to determine the grade give accurate grading solutions, at the cost of computation time. Other approaches have examined heuristic methods that implement key parts of the grading rules, or used artificial neural network methods, both with the loss of accuracy. Here, a different approach to computerized grading is examined that takes a hybridized approach using projected yield from cut-up simulation and neural network methods. This new hybrid approach has the advantage of both accuracy and high-processing speed. Such an approach lends itself to log sawing optimization with respect to NHLA grades and market values when internal log defect information is known.

1. Introduction

The quality and the market value of hardwood lumber is determined by the NHLA lumber grading rules (NHLA, 2104). In general, higher grade lumber, such as FAS, F1F, and Selects, has fewer defects and larger clear, defect free areas. Lower grade lumber, such as 1 Common, 2A Common, and 3A Common, has greater numbers of large defects and smaller clear areas. Overall, the hardwood lumber grading rules form a complex set of specifications that a board must meet to make a specific grade.

Computerized grading of hardwood lumber is not a new concept. The first work published regarding computerized grading on lumber was performed at the USDA Forest Products Laboratory in Madison, WI (Hallock and Galiger, 1971). Although this early program was accurate and fast, 10 boards per second, it was limited. The program could handle a maximum of 22 defects and graded the board as if all defects were on a single face. With the addition of the FAS One Face (F1F) and Selects lumber grades the rules became more complex, as they required grading each face separately.

Researchers at West Virginia University (WVU) sought to implement the full NHLA grading rules in a computer program. The ReGS (Realistic Grading System) program, a lumber grading training tool, (Klinkhachorn et al., 1994) exhaustively examined a board to determine the best clear cutting combination and lumber grade. UGRS (Moody et al., 1998) represented a more advanced approach to lumber grading training that also included remanufacturing to produce a higher lumber grade through edging, trimming, chopping, and ripping operations. Like ReGS, UGRS took an exhaustive approach to grading lumber with the full NHLA rule set. These programs graded lumber 100% accurate at the cost of execution speeds.

The complexity of the lumber grading rules and the number of cutting unit permutations that must be examined requires exhaustive approaches to lumber grading that demand significant computing time, like that of ReGS and UGRS. Thus, other approaches to lumber grading have been explored. Boden et al. (2005) developed a statistical approach to predicting the NHLA grade of lumber. Their main goal was the development of grading software that performed at faster speeds than programs that implemented the full rule set, like ReGS and UGRS. Boden et al.'s (2005) approach used three variables that described defect dispersion on the board surface and one variable summarizing defect size to develop a statistical model. The model achieved an overall accuracy of 73.4%, but graded boards 771 times faster than UGRS (Boden et al., 2005). However, the question remained whether or not mis-grading 26.4% of a lumber sample was acceptable.

E-mail address: ethomas@fs.fed.us

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Schmoldt (1995) proposed an artificial neural network (ANN) classifier approach to grading parts and lumber that would be suitable for real-time processing operations. The best performing neural network configuration achieved an accuracy of 61.5%. This network used standard back-propagation learning and consisted of 3 layers and 19 input nodes, 15 hidden layer nodes, and 5 output nodes. Both Schmoldt's (1995) and Boden et al.'s (2005) approaches grouped the upper grades: FAS, F1F, and Selects together and treated the common grades separately. Schmoldt's ANN approach also classified boards as below grade if they did not meet 3A Common specifications.

Training an ANN using back-propagation is a computationally intense process. With today's multi-core computer architectures this is less of a concern, it is now feasible to examine much larger ANN models that can accommodate many input variable combinations. Those combinations that lead to correct results (e.g., correct grade) are weighted heavier than those which don't. In this paper, the use of ANNs larger than those typically experimented with in the past is developed and tested for the grading of hardwood lumber. The goal of this ANN grading approach is to be able to accurately grade lumber within the log before sawing. Using laser scanning vision systems, the defects on the surface of a hardwood log can be detected (Thomas and Thomas, 2011) and the internal defect manifestations estimated (Thomas, 2016). Using this full defect information, log sawing can be optimized to return the highest NHLA grade and value of boards possible. However, to accomplish this, a fast and accurate computerized means of grading lumber is required.

2. Methods

Lumber from the kiln-dried hardwood lumber database (Gatchell et al., 1998) supplied boards for the development and testing data samples. The databank is composed of boards graded to FAS, F1F, Selects, 1 Common, 2A Common, and 3A Common NHLA grades. This database was repeatedly graded by different certified graders and all discrepancies between the graders adjudicated to the grading rules. This database also served as the "ground truth" for the development and testing of the ReGS (Klinkhachorn et al., 1994) and UGRS (Moody et al., 1998) hardwood lumber grading programs.

For this study, the entire database was utilized and a total of 4147 boards were selected for the development sample and 2137 boards for the testing sample. Boards were randomly selected from the entire database without replacement to create the development and testing samples. The numbers of boards by grade for the development and testing samples are listed in Table 1.

In earlier approaches to lumber grading software, the upper grades FAS, F1F, and Selects were combined into a single grade (Boden et al., 2005), or F1F and Selects were not considered (Schmoldt, 1995). An F1F board must meet the minimum size requirements for a FAS board: 6-in. by 8-feet, have one face that grades as FAS, and the back face meet 1 Common requirements. The Selects grade is virtually the same as F1F, except for the minimum board size required, 4-in. by 6-feet for Selects versus 6-in. by 8-feet for F1F. The Selects grade is more commonly traded in the Northern States and less often in the Southern and Appalachian regions (AHEC, 2008). In addition, rule 50 of NHLA grading rules state that Selects and 1 Common can be mixed and sold together (NHLA, 2014). Thus, for the purposes of this project, the 1 Common and Selects grades were combined for this study.

The Fast Artificial Neural Network (FANN) software was used to develop and test a variety of neural network configurations and topologies (Nissen, 2003). Standard reverse or back propagation training was used. A symmetric sigmoid activation function was used on the hidden nodes, while the standard sigmoid function was used for the output nodes. The best performing ANN has 19 input nodes, 2 hidden layers with 231 nodes each, and 5 output nodes. The ANN was allowed to train for a maximum of 8000 cycles (epochs) using the entire training set. The average training time for the neural network was approximately 1.25 h.

A special version of the ROMI rough mill simulator (Thomas et al., 2015) was developed to determine the yield potential and the sizes of clear cuttings that could be obtained from each board. This version of ROMI was heavily modified where many routines such as multiple part grade support and salvage processing (where additional rips and chops are required) were removed. These specific processing options are computational expensive and more importantly, primary processing for clear parts provides the best indicator of a board's quality. Thus, this modified version of ROMI is a method that quickly determines board yield. ROMI processes boards according to a cutting bill (e.g. a list of part sizes needed) and optimally fits the parts to the available clear, defect free areas. The larger the defect free areas, the larger the part sizes produced. To accommodate a variety of board qualities, the cutting bill consists of five widths (1.0, 1.5, 2.25, 2.75, and 3.5 in.), and eight lengths (10, 15, 18, 21, 27, 33, 39, and 53 in.). Numerous part sizes and numbers of parts were experimented with. In the end, this simple cutting order consisting of a full range of part widths and lengths proved to be good predictors of grade.

Table 2 lists the data associated with each specific input and output node. Perhaps the most critical inputs are 3 and 4, primary part yield and average part size, respectively, determined by the ROMI simulator. Additional inputs to the ANN consisted of the width and length of the board. Board dimensions are a simple discriminator for determining if a board is FAS or F1F. The remaining 15 inputs characterize the size and count of the different defect types. According to the NHLA grading rules (NHLA, 2014), depend-

Table 1
Board counts by grade for the development and testing samples.

Lumber grade	Development sample	Testing sample
FAS	876	432
F1F	455	245
1C/Selects	1513	815
2A Common	1071	499
3A Common	232	146
Total	4147	2137

Table 2
Data description of artificial neural network input and output nodes.

Node	Input node description	Output node description
1	Board width (in.)	FAS grade probability
2	Board length (in.)	F1F grade probability
3	Primary part yield	1C/Selects grade probability
4	Average part size	2A grade probability
5	Total defect count	3A grade probability
6	Sound knot defect count	
7	Total sound knot area	
8	Unsound knot defect count	
9	Total unsound knot area	
10	Decayed area defect count	
11	Total decayed/rotten area	
12	Hole defect count	
13	Total hole surface area	
14	Pith defect count	
15	Total pith surface area	
16	Split defect count	
17	Total split surface area	
18	Total length lower edge wane	
19	Total length upper edge wane	