MODELING TECHNOLOGY ADOPTION IN THE HARDWOOD SAWMILL

Scott A. Bowe†

Assistant Professor and Wood Products Specialist
Department of Forest Ecology and Management
College of Agricultural and Life Sciences
University of Wisconsin-Madison
120 Russell Labs
1630 Linden Drive
Madison, WI 53706-1598

and

Robert L. Smith†

Professor and Director
Center for Forest Products Marketing and Management
Department of Wood Science and Forest Products
College of Natural Resources
Virginia Polytechnic Institute and State University
Blacksburg, VA 24061

(Received April 2005)

ABSTRACT

This study examined the adoption decision process for scanning and optimizing technology in hardwood sawmills. Data were collected through personal interviews with two hardwood sawmill groups including those that had adopted advanced scanning and optimizing technology and those that had not adopted such technology. The interviewees rated the importance of decision factors in the adoption decision process. They also rated the influence of four sawmill departments on the adoption decision process. These data were compiled using the Analytic Hierarchy Process model. The initial premise that adopters of scanning and optimizing technology managed from a systems perspective was not found. When examining the influence of the four sawmill departments in the adoption decision process, technology adopters rated the *production process* more than two times higher than the next highest department. Non-adopters also rated the *production process* the highest; however, the overall rating of the four sawmill departments' influence was more evenly weighted in the non-adopter model.

Keywords: Hardwood sawmill, scanning, optimizing, technology, adoption, analytic, hierarchy, process.

INTRODUCTION

In recent years, the forest products industry in the United States has faced increased competition from overseas manufacturers. Manufacturers in countries such as China have won contracts with American distributors and retailers based on price and quality. American manufacturers have been scrambling to try and remain competitive (Buehlmann et al. 2003). Changes in management systems and processing technology are some of the many process improvement strategies being implemented by US wood products firms today. Terms such as *lean manufacturing* and *systems approach* are common in the vocabulary of firms that are dedicated to continuous improvement in their organizations.

Have primary producers such as sawmills adopted a similar strategy? Are sawmills examining their businesses from a broader systems

† Member of SWST.

Wood and Fiber Science, 38(3), 2006, pp. 484–496

perspective? Are sawmills considering new technology in their process improvements? This study examined the decision-making process of hardwood sawmills as they considered investment in scanning and optimizing technology. Scanning and optimizing technology refers to the systems that scan lumber for defects and optimize value in processing based upon that defect information. Examples of such technology include edger optimizer and trimmer optimizer systems.

Two distinctly different groups of hardwood sawmills were included to identify differences in their decision processes. These groups included hardwood sawmills that have already installed scanning and optimizing technology and hardwood sawmills that have yet to install scanning and optimizing technology. The initial premise of this study was that those sawmills with scanning and optimizing technology were more innovative and more inclined to manage their sawmills from a broader systems perspective. These sawmills would view input from their various departments more equally. The departments, as defined by the study, included *log procurement*, *production process*, *sales and marketing*, and the *customer*. In contrast, sawmills that had not adopted scanning and optimizing technology were thought to be less innovative and less likely to manage from a systems perspective.

The modeling technique used in this study was the Analytic Hierarchy Process (AHP). The AHP model is a mathematical theory for measurement and decision-making that was developed during the mid-1970s (Expert Choice 1999). The strength of this modeling process is in its ability to analyze complex decision problems. It organizes the basic rationality by breaking a problem into its smaller constituent parts and uses simple pair-wise comparison judgments to develop priorities in each hierarchy (Harker and Vargas 1987). As a final step, the model generates a series of weights, which identify the most important constituent parts in the decision process.

Manufacturing technology often presents some difficult choices. Scanning and optimizing technology such as edger-optimizers are one such example. The adoption process involved with this technology is unclear. What processes do sawmill managers go through when they are considering the purchase of scanning and optimizing technology? What characteristics of the technology influence the decision process? What characteristics of the hardwood sawmill influence the decision process? What role does communication within the sawmill play in the decision process? These questions were examined with the AHP model.

OBJECTIVES

The objectives of this study were to 1) determine the important decision factors for the adoption of scanning and optimizing technology in hardwood sawmills, and 2) using the Analytic Hierarchy Process, examine these decision factors based on a sawmill systems perspective.

METHODS

Population

The population of interest was defined as hardwood sawmills. However, this population was divided into two groups: hardwood sawmills that have adopted scanning and optimizing technology and hardwood sawmills that have not adopted such technology.

Sample frame

To construct the model, data from a previous study by the authors were used (Bowe et al. 2002). The previous study consisted of a nationwide mail survey of technology use in hardwood sawmill industry. Input data to run the model were collected from a subset of these hardwood sawmills. This subset included 11 hardwood sawmills that had adopted advanced scanning and optimizing technology and 16 hardwood sawmills that had not adopted advanced scanning and optimizing technology. The sampling process was not random, but purposeful in nature. Patton (1990) identifies several sampling procedures. One such procedure called stratified purposeful sampling illustrates characteristics of particular subgroups of interest to facilitate comparisons. This was the principle behind selecting two groups, adopters and non-adopters. It is also important to note that these 27 hardwood sawmills were located in 7 states including Wisconsin, Virginia, West Virginia, Maryland, Pennsylvania, Tennessee, and North Carolina, which covered the primary hardwood producing regions within the United States. This resulted in models that were based on national data. The geographically broad sample area was also needed to identify a sufficient number of hardwood sawmills that had already invested in scanning and optimizing technology.

AHP model development

The development of the AHP model involved several steps including factor reduction and model construction. Each step was dependent upon the previous to build the model's theoretical foundation.

Factor reduction

As described above, a nationwide mail survey was conducted in the fall of 1999 (Bowe et al. 2002). Questionnaires were sent to more than 2000 hardwood sawmills. Information was collected on hardwood sawmill demographics and production. In addition, seven-point Likert scales were used to collect information on scanning and optimizing technology. The mail survey scale question, which was used to build the AHP model, examined edger-optimizer systems. Respondents rated the importance of 20 factors involved in their decision to purchase or not purchase edger-optimizer systems (Table 1).

The AHP model structure used in this research is capable of incorporating up to nine decision factors. As the number of decision factors increases, so does the number of paired comparisons. Beyond the nine-factor limit, the number of comparisons becomes difficult for a respondent to perform in a reasonable amount of time in a meaningful manner. It was necessary to condense the number of decision factors shown in Table 1 but still maintain their underlying meaning. To accomplish this, factor analysis was used. Factor analysis identifies underlying factors that explain the pattern of correlation within a set of observed variables (Hair et al. 1992). In our case, correlated adoption decision factors were identified. The principal component analysis method with varimax rotation was used. The principal component procedure was chosen for its ability to summarize the original information (20 factors) into a minimum number of factors while maintaining most of the original information. Varimax rotation was chosen to provide a clearer separation of the factors (Hair et al. 1992). The resulting analysis reduces the number of factors to six including *equipment features*, *production improvements*, *mill communications*, *maintenance issues*, *barriers*, and *customer requirements*. The SPSS® Statistical Data Analysis package was used to perform the analysis (SPSS 2001).

TABLE 1. *Factor importance ratings for current edger-optimizers.*

Factor	Mean importance
Improved raw material recovery	6.5
Increased lumber revenues	6.5
System lifespan	6.0
Improved lumber quality	5.9
Ability to upgrade	5.9
Availability of vendor support	5.8
Increased production levels	5.8
Improved lumber consistency	5.7
Ease of use	5.7
Initial cost	5.7
Maintenance costs	5.2
Existing mill layout restrictions	5.2
Training from vendor	5.1
Operational costs	5.1
Installation downtime	4.8
Advice from production supervisors	4.7
Training of new operators	4.6
Advice from customers	4.4
New mill installation	4.1
Advice from sales department	3.7

Model construction

The AHP modeling process can be broken into three principal processes, which include decomposition, comparative judgments, and synthesis of priorities (Harker and Vargas 1987). These three steps are key in the modeling process. Decomposition allows for a complex decision problem to be broken into simple manageable parts. The comparative judgments process results in the formation of a matrix from pair-wise comparisons of the relative importance of the elements in one hierarchy level with respect to the elements one level up. The synthesis process generates a composite of the elements at the lowest hierarchy level (Harker and Vargas 1987). Figure 1 provides an example of the AHP model applied to the scanning and optimization technology adoption process. It illustrates the three-step modeling process of decomposition, comparative judgments, and synthesis of priorities.

Decomposition.—Figure 1 can be broken into four major levels including the goal level, the decision-makers level, the decision factors level, and the sawmill departments level. The goal level describes the decision under investigation. In our model, the goal was to determine the level of sawmill department influence in the decision to adopt scanning and optimizing technology in the hardwood sawmill. In other words, how influential are the opinions of the different sawmill departments.

The second level is the decision-makers level. In our case, the decision-makers level is comprised of two groups: hardwood sawmills that have adopted scanning and optimizing technology and hardwood sawmills that have not adopted such technology.

The third level consists of the adoption decision factors or criteria that are important in the decision process. These were generated by the factor analysis of the mail survey data. At this level, the respondents made a series of pair-wise comparisons between each of the six decision factors, which in turn weight the decision factors as to their importance (Fig. 1). The weights across all decision factors sum to one.

Level four, the sawmill departments level, is key for the sawmill systems analysis. Level four describes a generic way of viewing a typical sawmill, which includes log procurement, production process, sales and marketing, and the customer. At this level, the respondents made a series of pair-wise comparisons between each of the four sawmill departments as they are influenced by each decision factor one level up. Pair-wise comparisons are performed six times, one for each decision factor (Fig. 1).

Comparative judgments.—The decomposition process clearly demonstrates the hierarchy within the AHP model. The comparative judgment process demonstrates the role of pair-wise comparisons in the decision process (Fig. 1). These pair-wise comparisons generate the data

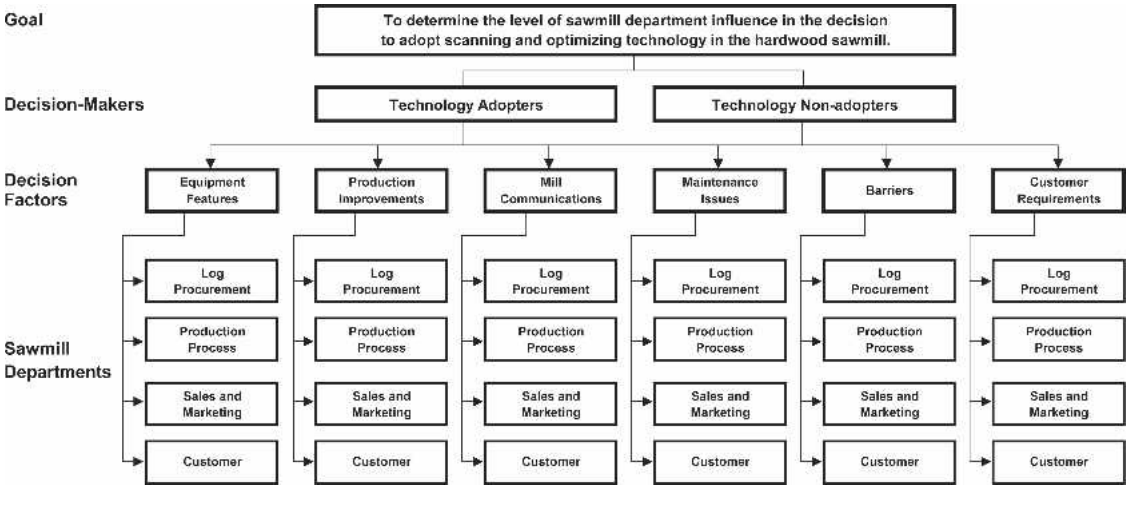

FIG. 1. AHP model structure, scanning and optimizing technology example

to build the vectors and matrices needed in the synthesis of priorities, the final step of the AHP modeling process.

The first matrix results from the pair-wise comparisons at the decision factors level. This matrix is called the decision factor priority vector. In our case, this vector is a 6×1 matrix of values that weight the importance of each decision factor relative to one another.

The second matrix results from the pair-wise comparisons at the sawmill departments level with respect to each decision factor one level up. In our case, this matrix is called the sawmill department priority vector. This vector is a 4×6 matrix of values that weight the importance of each sawmill department relative to one another with respect to each decision factor. To achieve the desired outcome, this vector is normalized during the AHP modeling process.

Synthesis of priorities.—The synthesis process weights the elements at the lowest hierarchy level, the sawmill departments level. These weight values are called the final preference vector. The final preference vector results from the multiplication of the decision factor priority vector (matrix 1) with the sawmill department priority vector (matrix 2). This results in a 4×1 matrix. The final preference vector satisfies the model goal. It weights each sawmill department based on its influence in the decision to adopt scanning and optimizing technology.

Data collection

The data collection during the case studies involved personal interviews at the participating hardwood sawmills. Interviews were scheduled with the primary equipment decision-maker at the sawmill. In most cases the primary equipment decision-maker was the sawmill owner or the sawmill manager. The meeting typically lasted less than one hour; however, several mill visits lasted several hours. In those cases, the interviewee spent a great deal of time describing the sawmill and his experience or opinions of scanning and optimizing technology. Many of the interviews also included a mill tour, which added to the qualitative value of the interview.

Each interview opened with an explanation of the research project. Several open-ended questions were asked to put the interviewee at ease. Following the open-ended questions, the interviewee was asked to complete a written questionnaire. Fifty-one paired comparisons were made by the interviewee including 15 at the decision factors level and 36 at the sawmill departments level. The questionnaire was developed directly from the model shown in Fig. 1. The questionnaire and the interview format were successfully pre-tested with five hardwood sawmills located in Virginia and West Virginia.

Data analysis

The AHP model uses matrix algebra to solve the decision objective. Expert Choice™ is a PC driven decision support software package built for the AHP modeling process (Expert Choice 1993). A model as shown in Fig. 1 was constructed within the Expert Choice program. This model incorporated data from the advanced scanning and optimizing adopters and non-adopters. The pair-wise comparisons from the written interview questionnaire forms were entered into the model in Expert Choice. Expert Choice was then used to generate the final preference vectors and to conduct sensitivity analysis.

Inconsistency ratios

For each set of pair-wise comparisons performed, Expert Choice provided a rating called an inconsistency ratio. This ratio is a measure of how consistent the respondent was in his or her pair-wise ratings. For example, if A was rated 2 times greater than B, and B was rated 2 times greater than C, then A should be rated 4 times greater than C. There is a certain amount of inconsistency in any respondent's answers. Saaty (1980) suggests that an inconsistency ratio of less than 0.1 is excellent. In both the adopter and non-adopter models, the inconsistency ratios were 0.03 or lower.

TABLE 2. *Factor reduction and classification.*

Factor 1 (.85) equipment features	Factor 2 (.81) production improvements	Factor 3 (.74) mill communications
Training from vendor	Improved raw material recovery	Advice from sales department
Ease of use	Increased production levels	Advice from customers
Availability of vendor support	Increased lumber revenues	Advice from production supervisors
Ability to upgrade	Improved lumber quality	
System lifespan	Improved lumber consistency	
Factor 4 (.77) maintenance issues	**Factor 5 (.43) barriers**	**Factor 6 customer requirements**
Training of new operators	Initial cost	Size requirements
Operational costs	New mill installation	Grade requirements
Installation downtime	Existing mill layout restrictions	Sorting requirements
Maintenance costs		

* Cronbach's alpha values for each factor grouping are shown in parentheses

TABLE 3. *Decision factor priority vector.*

Decision factors	Priority vector
Equipment features	0.114
Production improvements	0.286
Mill communications	0.075
Maintenance issues	0.206
Barriers	0.112
Customer requirements	0.207

RESULTS AND DISCUSSION

Factor reduction results

Factor analysis was used to reduce the number of decision factors from the mail survey. Correlated adoption decision factors were identified. Using the principal component analysis method with varimax rotation, five underlying components were identified. To determine which components (column) a factor loaded into, a minimum significance level of 0.3 was established; however, no factor in our analysis loaded below 0.5. A general rule states that 0.3 is significant, 0.4 is more important, and 0.5 is very significant (Hair et al. 1992). The original 20 factors were organized into five groups as dictated by their loadings (Table 2). After the groups were determined, appropriate decision factor names were added. These final decision factor names included *equipment features*, *production improvements*, *mill communications*, *maintenance issues*, and *barriers*.

Review of these five factors found that each was closely related to production. The intent of the model was to examine the hardwood sawmill from a systems perspective; therefore, a sixth factor, *customer requirements*, was added to expand the scope of the model to its original intent (Table 2). Since the AHP model anatomy considers each factor independently, any of these six factors could be removed to determine how the model performs in its absence.

Modeling example

The following example demonstrates the AHP. Data from the advanced scanning and optimizing technology *adopters* are used below to show how the synthesis of priorities was calculated.

The *decision factor priority vector* results from the pair-wise comparisons at the decision factor level. This vector is a 6 × 1 matrix of values that weights the importance of each decision factor relative to one another (Table 3). These individual weights are normalized to provide a relative scale. Normalization assures that the final weights sum to one.

The *sawmill department priority vector* results from the pair-wise comparisons at the sawmill departments level with respect to each decision factor one level up. This vector is a 4 × 6 matrix of values that weights the importance of each sawmill department relative to one another with respect to each decision factor. To achieve the desired outcome, this vector is normalized during the AHP modeling process (Table 4).

TABLE 4. *Sawmill department priority vector.*

	Decision factors					
Sawmill department	Equipment features	Production improvements	Mill comm.	Maintenance issues	Barriers	Customer requirement
Log procurement	0.012	0.039	0.010	0.020	0.016	0.023
Production process	0.044	0.150	0.036	0.125	0.066	0.044
Sales and marketing	0.032	0.052	0.016	0.037	0.018	0.069
Customer	0.027	0.045	0.012	0.024	0.014	0.071
	Normalized decision factors					
Sawmill department	Equipment features	Production improvements	Mill comm.	Maintenance issues	Barriers	Customer requirements
Log procurement	0.104	0.136	0.135	0.097	0.140	0.111
Production process	0.383	0.524	0.486	0.607	0.579	0.213
Sales and marketing	0.278	0.182	0.216	0.180	0.158	0.333
Customer	0.235	0.157	0.162	0.117	0.123	0.343

The *final preference vector* results from the multiplication of the *decision factor priority vector* (Table 3) with the *sawmill department priority vector* (Table 4). The *final preference vector* is a 4 × 1 matrix that holds the composite priorities at the model's lowest level, the sawmill departments. Figure 2 shows the multiplication process that generates the *final preference vector*.

MODEL RESULTS

Decision factor priority vectors.—The decision factor priority vector weights the model decision factors by their importance. The higher the weighting, the more important that decision factor was in the overall model decision. Figure 3 provides the decision factor priority vectors for the adopter and non-adopter models.

Production improvements was rated highest for adopters. If we examine the original corresponding factors, *increased lumber revenues*, *increased production levels*, and *improved raw material recovery* were all highly rated factors in the mail survey portion of this research. Several differences are evident between the adopter and non-adopter groups. *Production improvements* was rated higher for adopters than the non-adopters. This was contrary to the expected results. It was initially expected that the adopters were managed more from a systems perspective.

$$
\begin{array}{l}
\\
\text{Log Procurement}\\
\text{Production Process}\\
\text{Sales and Marketing}\\
\text{Customer}
\end{array}
\begin{array}{cccccc}
\text{Equipment Features} & \text{Production Improvements} & \text{Mill Communications} & \text{Maintenance Issues} & \text{Barriers} & \text{Customer Requirements}\\
\end{array}
$$

$$
\underbrace{\begin{pmatrix}
0.104 & 0.136 & 0.135 & 0.097 & 0.140 & 0.111\\
0.383 & 0.524 & 0.486 & 0.607 & 0.579 & 0.213\\
0.278 & 0.182 & 0.216 & 0.180 & 0.158 & 0.333\\
0.235 & 0.157 & 0.162 & 0.117 & 0.123 & 0.343
\end{pmatrix}}_{\text{Sawmill Department Priority Vector}}
\underbrace{\begin{pmatrix}
0.114\\ 0.286\\ 0.075\\ 0.206\\ 0.112\\ 0.207
\end{pmatrix}}_{\text{Decision Factor Priority Vector}}
=
\underbrace{\begin{pmatrix}
0.120\\ 0.463\\ 0.224\\ 0.192
\end{pmatrix}}_{\text{Final Preference Vector}}
\begin{array}{l}
\text{Log Procurement}\\
\text{Production Process}\\
\text{Sales and Marketing}\\
\text{Customer}
\end{array}
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FIG. 2. Final preference vector, adopter results

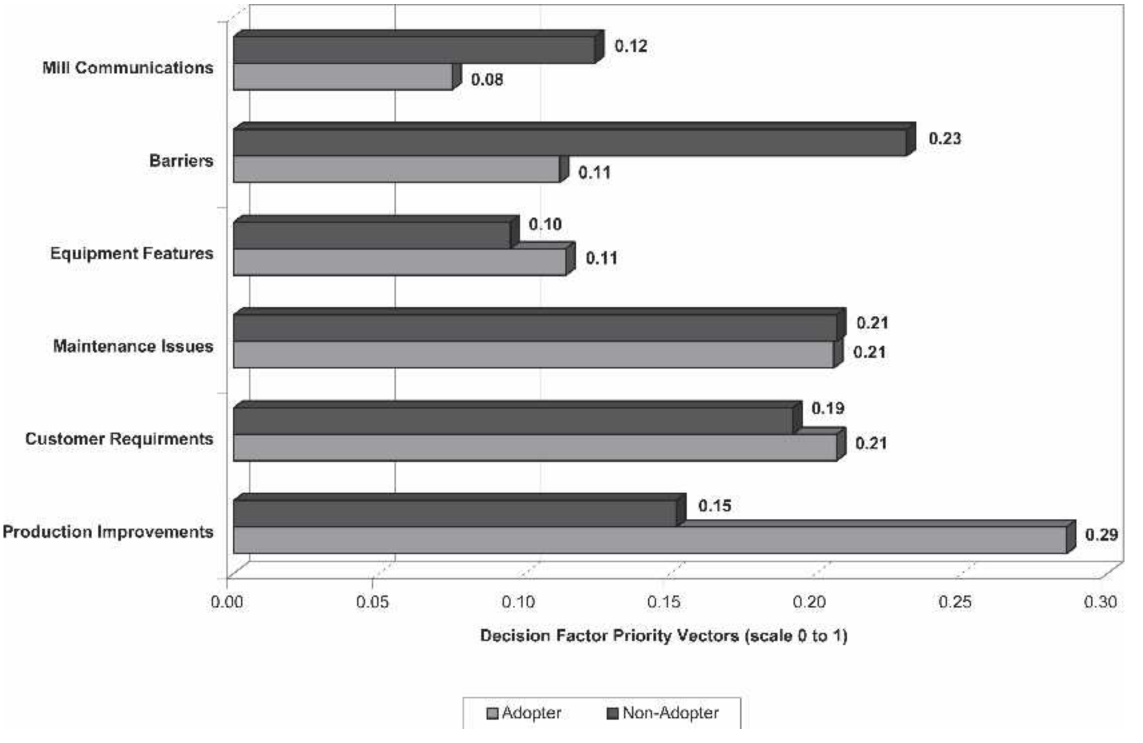

FIG. 3. Adopter and Non-Adopter decision factor priority vectors

Here increased production would be a result of this management philosophy and not a driver of it. *Mill communications* is higher for non-adopters. This is also contrary to the expected results. This could be explained by the fact that many of the non-adopters were small companies. The mill owner or manager often serves many roles in these companies and is in constant contact with the employees throughout the sawmill. *Barriers* was rated higher by the non-adopters. Two factor components for *barriers* were *initial cost* and *existing mill layout restriction*. The large capital requirements for the purchase of future scanning and optimizing technology restrict many small companies. In addition, the large size of this equipment may prohibit small mills from adopting it because of space restrictions. *Equipment features*, *maintenance issues*, and *customer requirements* were rated similarly for adopters and non-adopters (Fig. 3). It is important to note that c*ustomer requirements* was highly rated. This adds validity to our decision to include this decision factor.

Final preference vectors.—The final preference vector weights the sawmill departments by their overall influence in the decision to adopt or not adopt future scanning and optimizing. The higher the weighting, the more important that department was in the overall adoption decision (Fig. 4).

Paralleling the decision factor priority vector results, *production process* (the production department) was rated the highest by adopters and non-adopters. This supports the production philosophy in the wood products industry. It was initially expected that the adopters were managed more from a systems perspective. In other words, the four department ratings would be more evenly distributed for the adopters than the non-adopters. In fact, the opposite was true. Non-adopters rated the four sawmill departments more evenly than the adopters. As with the decision factor priority vectors, this could be a result of sawmill management anatomy. The owner or sawmill manager of a small sawmill is in contact with or is the primary em-

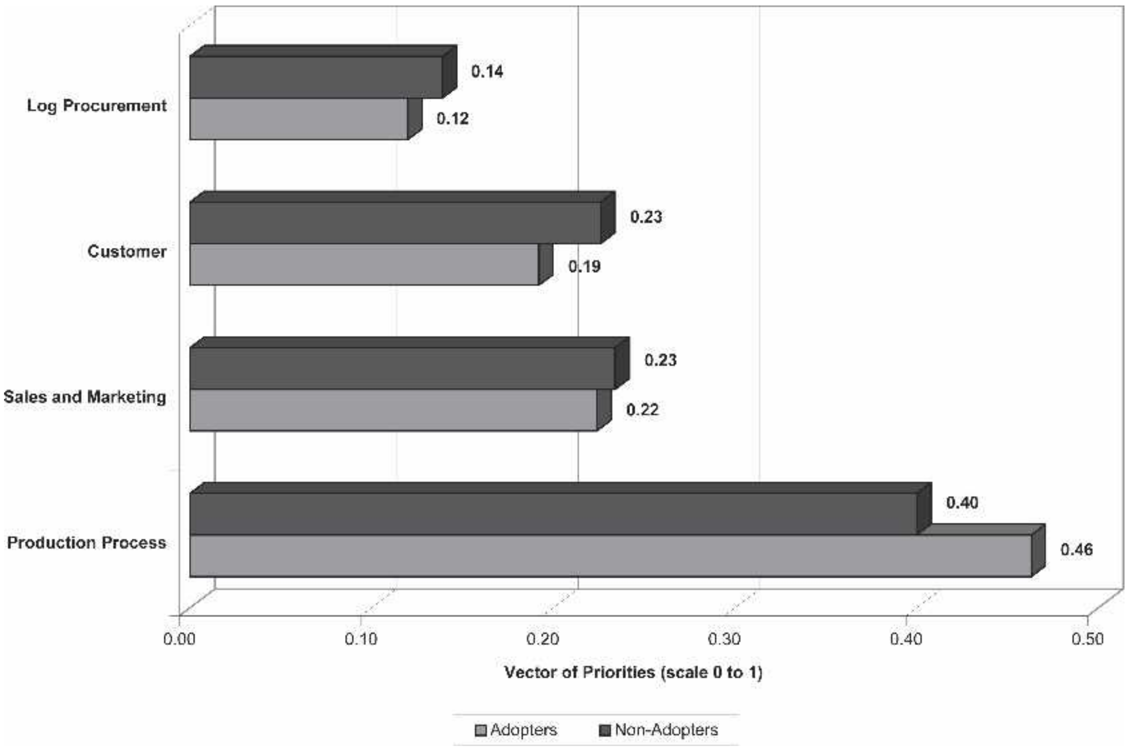

FIG. 4. Influence of sawmill department: Adopters versus Non-Adopters

ployee in many or all of these departments. This individual may view each department more equally.

Compiled models.—To summarize the data for adopters and non-adopters, Fig. 5 provides the final AHP model structure for adopters and non-adopters. Decision factor priority vectors and sawmill department priority vectors are shown. The model follows the same structure shown in Fig. 1, and provides the final decision values for the two groups.

Figure 5 depicts the data at a more detailed level. We are able to see each department's influence with respect to each decision factor. It was stated earlier that the *production process* department was found to be more influential with the adopter group. This is shown in more detail with the department weights represented for each decision factor. A similar but opposite trend is shown for the *log procurement* department in the non-adopter group.

Sensitivity analysis

Sensitivity analysis is used to investigate the sensitivity of the sawmill departments to changes in the priorities of the decision factors. In other words, will a sawmill department become more influential in the decision to adopt future scanning and optimizing technology if certain decision factors become more or less important?

Adopters.—Figure 6 graphically represents sensitivity analysis for the adopters group. The vertical line represents the decision factor under analysis. As this decision factor becomes more important (i.e. moved right on the X-axis), its intersection with the slope of the four sawmill department lines show if the departmental influence increases or decreases.

As the decision factor, *customer requirements*, becomes more important, the sales and marketing and the customer departments become more influential while the production pro-

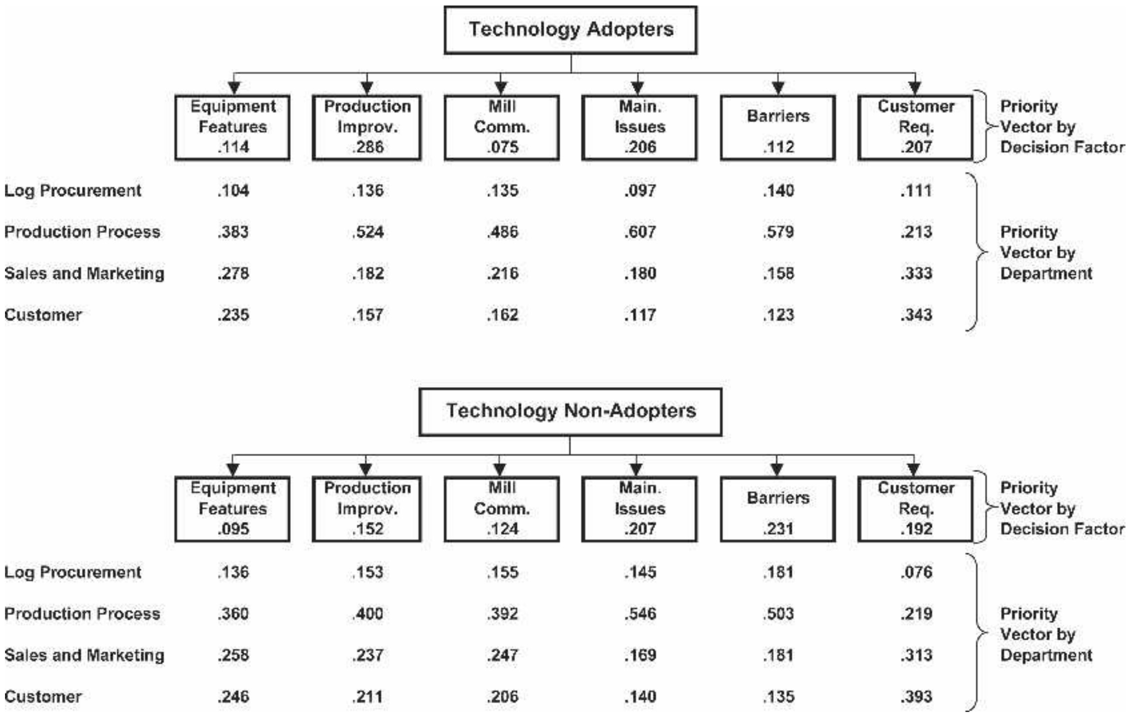

FIG. 5. Final AHP decision models for technology Adopters and Non-Adopters

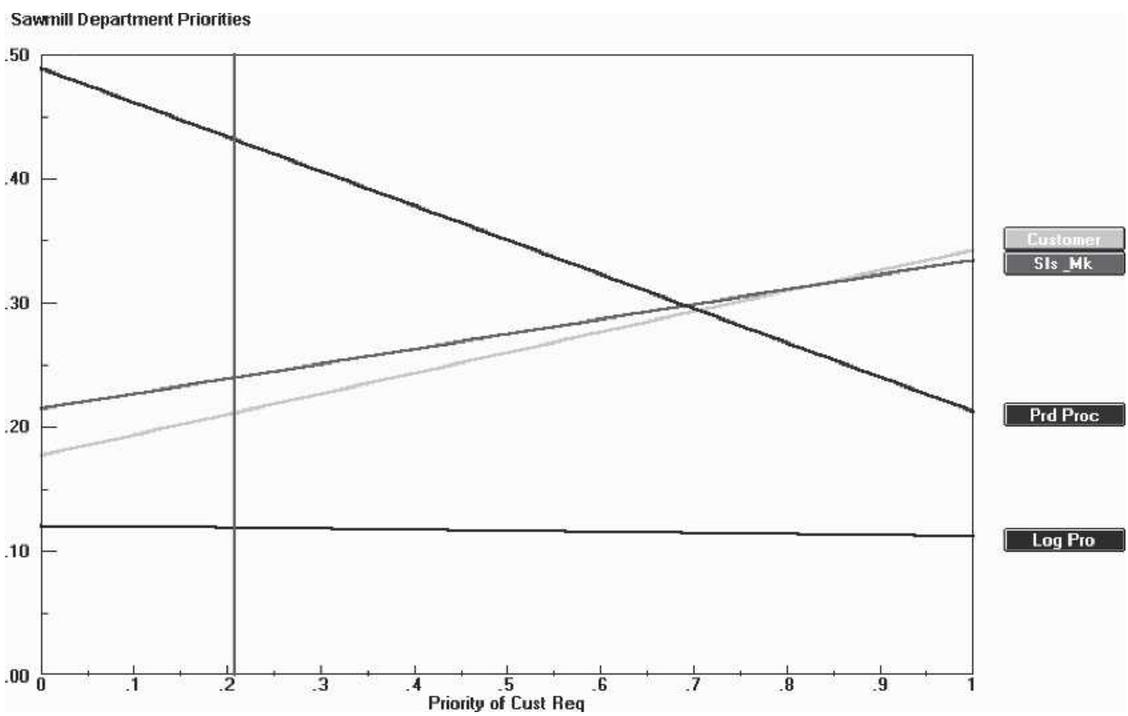

FIG. 6. Adopter sensitivity analysis for customer requirements

cess and the log procurement departments become less influential (Fig. 6). At high importance levels of *customer requirements*, the influence of the production process department falls below the customer and the sales and marketing departments. If customer requirements are paramount in cases such as custom sorting or packaging, the production department becomes less influential. The large negative slope of the production process department may demonstrate the importance of the customer, despite the overall production emphasis.

Non-adopters.—Figure 7 graphically represents sensitivity analysis for the non-adopters group. As the decision factor, *customer requirements*, becomes more important, the sales and marketing and the customer departments become more influential while the production process and the log procurement departments become less influential (Fig. 7). These results are similar to the adopter model. If customer requirements are paramount in cases such as custom sorting or packaging, the production department becomes less influential, and the customer's needs (influence) surpasses the production department.

CONCLUSIONS

The AHP was an effective modeling tool for the hardwood sawmill industry. This model was chosen specifically for its ability to examine hardwood sawmills from a system perspective. A hardwood sawmill managed as a system would demonstrate interdepartmental cooperation where the sawmill is viewed as a whole and not as individual parts. An initial premise of this research was that those sawmills with scanning and optimizing technology were more innovative and more inclined to manage their sawmills from a systems perspective. These sawmills would view log procurement, the production process, sales and marketing, and the customer more equally. In contrast, sawmills that had not adopted advanced scanning and optimizing technology were thought to be less innovative and

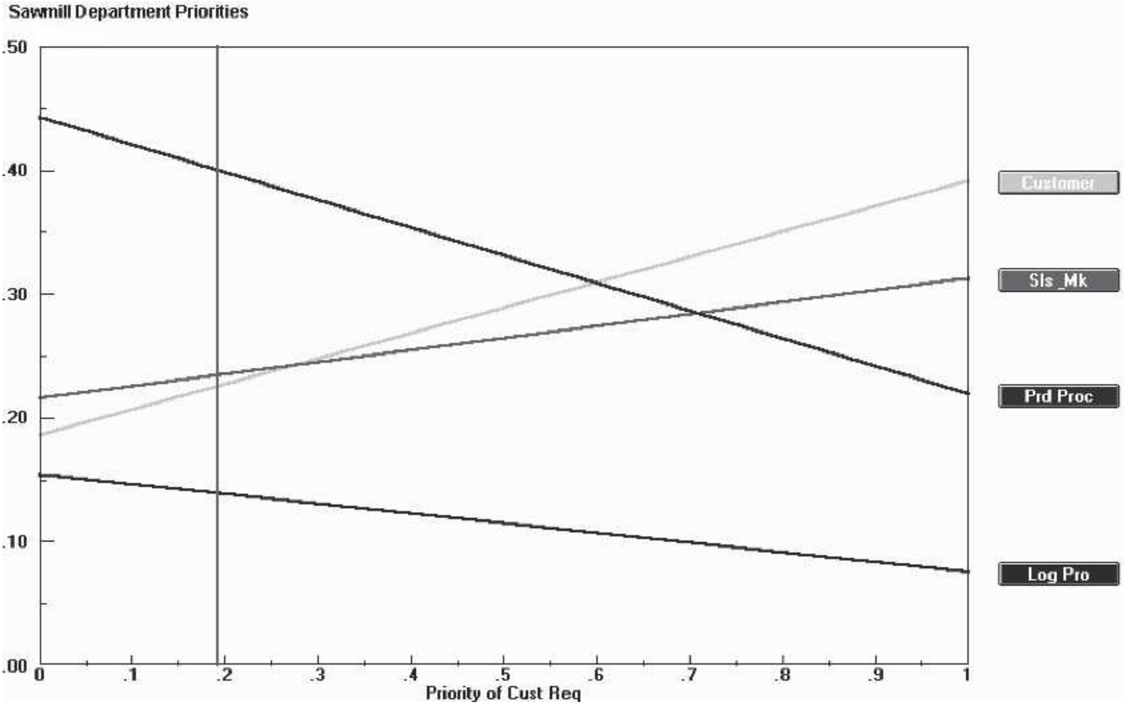

FIG. 7. Non-adopter sensitivity analysis for customer requirements

less likely to manage from a systems perspective.

Overall, the initial premise that adopters of scanning and optimizing technology manage from a systems perspective was not found. When examining the influence of the four sawmill departments in the adoption decision process, adopters rated the *production process* more than two times higher than the next highest department. Non-adopters also rated the *production process* the highest; however, the overall rating of the four departments' influence was more evenly distributed in the non-adopter model. The *log procurement*, *customer*, and *sales and marketing* departments were all rated higher by the non-adopters versus the adopters.

With respect to the decision factor ratings, adopters rated *production improvements* as the most important decision factor. This was followed by *customer requirements* and *maintenance issues*. In contrast, non-adopters rated *barriers* as the most important decision factor followed by *maintenance issues* and *customer requirements*. *Production improvements* was rated fourth by the non-adopters.

Overall, adopters rated production as the most important decision factor and sawmill department. Their general management philosophy could be described as a production orientation. The installation of future scanning and optimizing technology by adopters will likely be done to satisfy a production objective not a systems improvement objective. The *maintenance issues* decision factor was highly rated by both adopters and non-adopters. Chronic maintenance problems soon become production issues. The decision factor *customer requirements* was highly rated by both adopters and non-adopters. This may demonstrate that customer requirements are considered in the production process. This would be reasonable since they are the end user. In addition, the high rating of *customer requirements* validates the decision to include it as a decision factor. Finally, *barriers* was rated as the highest decision factor for non-adopters. Many of the non-adopters were small companies where the high initial cost of future scanning and optimizing technology would be prohibitive.

Sawmill management anatomy may have played a role in the outcome of the adopter and non-adopter models. The owners or managers of small hardwood sawmills (non-adopters) frequently perform many functions within the sawmill. They may procure logs, work in production, perform maintenance, and sell the final product. This wide-ranging job description would give them a systems view of the sawmill. This may explain the more evenly rated model. Mill managers of large sawmills (adopters) are often concerned only with the production process in a sawmill. This may explain the production orientation in the final model.

This research found firms that have adopted currently available technology were more likely to be production oriented. In other words they have incorporated technology not because of their quest for total system improvements, but for gains in production. In promoting scanning and optimizing technology, high production firms and/or current technology-using firms should be targeted as early adopters. The users of current technology have already demonstrated their willingness to adopt a technology to improve their production. The high production non-adopters could be persuaded to do so if the production benefits of this technology could be demonstrated. Barriers such as cost are important in the decision process. A significant segment of the hardwood sawmill industry will not consider such technology if cost barriers are not addressed.

ACKNOWLEDGMENTS

This research project was supported by the USDA Southern Research Station and the USDA National Needs Fellowship Program. The authors would like to thank these institutions for their support and thank the individuals that participated in the project.

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