

THE LEAN INDEX: OPERATIONAL “LEAN” METRICS FOR THE WOOD PRODUCTS INDUSTRY

Charles D. Ray†

Assistant Professor

Xiaoqiu Zuo

Post-Doctorate Research Assistant

Judd H. Michael

Associate Professor

School of Forest Resources

The Pennsylvania State University

University Park, PA 16802-4705

and

Janice K. Wiedenbeck†

Research Forest Products Technologist

Forestry Sciences Laboratory

The U.S. Forest Service

Princeton, WV 24740

(Received March 2005)

ABSTRACT

No standard definition for lean production exists today, especially specific to the wood products industries. From a management point of view, even the more straightforward management issues surrounding the concept of “lean” are complex. This exploratory research seeks to develop a methodology for quantitative and objective assessment of the leanness of any wood products operation. Factor analysis is a statistical approach that describes the patterns of relationships among quantifiable predictor variables, with the goal of identifying variables that cannot be directly measured, such as the leanness of a company. Using this technique, a factor model was identified and a factor score, or “Lean Index,” was developed. For the nine wood products companies included in this study, the average Lean Index is demonstrated to be 5.07, ranging from a low of 2.33 to a high of 12.00. Based on the quantified standards of lean production developed in this study, (1) primary wood products operations are inherently leaner than secondary wood products operations; (2) process throughput variables explain approximately twice the total variance of all consumed resources, compared to process support variables; and (3) energy consumption is shown to be the single most significant contributor to the leanness of any wood products company.

Keywords: Business metrics, factor analysis, lean production.

INTRODUCTION

“Lean manufacturing” or “lean production” has become the de facto standard for companies trying to upgrade their competitive capabilities

in today’s global market. The term “lean production” first appeared in *The Machine That Changed The World* (Womack et al. 1990), in which the authors coined the term to describe the strategic business system and operational differences between Japanese auto producers and North American auto producers of the 1980s. As

† Member of SWST.

various authors and consultants studied the individual components of the Japanese “lean” systems, they identified several distinct and unique areas of focus for implementing lean manufacturing: for example, just-in-time production, set-up reduction, total productive maintenance, and the “5S” (Sort, Straighten, Shine, Standardize, and Sustain) system.

Lean manufacturing is a corporate activity of continuous improvement and requires effective strategies to successfully implement. Experience from lean implementation efforts shows that these specific business strategies are significantly impacted by the stage of manufacturing (Nightingale and Mize 2002). A good strategy needs to be defined and redefined dynamically according to the current circumstances of manufacturing during lean implementation (Kesser 1999; Nightingale and Mize 2002; Wilson and Pearson 1995). An effective assessment tool, therefore, plays a vital role in evaluating each stage of manufacturing and further in determining the strategy and priorities of lean implementation (Wilson and Pearson 1995).

A principal tenet of lean manufacturing is to eliminate waste in all its forms, of which one of the primary is *inventory*. Through pull-type lean production techniques, called kanban systems, firms learn to produce only those components needed for the current production or order file. In manufacturing products that utilize homogeneous raw material (such as steel for automobiles) kanban works well; parts are machined from the raw steel stock as required, waste stock gets recycled back into the process, and the remaining stock awaits the next call from the system.

Many wood products companies have adopted or are considering adopting full or partial lean components. The most successful wood products company in utilizing lean production techniques may be the Merillat Industries Door and Panel Plant in Atkins, Virginia. The company, which won the Shingo Prize (for lean manufacturing performance) in 2003, achieved 99.7% on time delivery, reduced cycle time from over 5 days to 17 hours, reduced WIP by over 80% and

reduced total cost by 7.1% from implementation of lean strategies (Shingo Prize 2003).

In recent years, the general concept of lean operation modeled after the Toyota Production System (see Ohno 1988) has been instructed and accepted in many wood products companies. However, Kenney and Florida (1993) pointed out that not every company may realize the same dramatic benefits from lean production as Toyota. Specifically, for hardwood products manufacturers, raw material (lumber) cost accounts for more than 50% of total production cost. Customer-driven inventory practices, that is, restriction of lumber or component production to current order requirements, could result in the disposal of clear wood not required by the customers, which increases the material cost significantly through yield loss. This unique feature of wood products processing can lead to conflicts among wood recovery, inventory, and cost when wood products companies attempt to adopt lean techniques. Therefore, questions about lean manufacturing in wood products arise:

1. How is the leanness of a wood products company properly measured?
2. How does a lean wood products company perform compared to a non-lean producer of wood products?
3. Where are the points of differentiation between lean and non-lean systems?
4. Which lean elements should be adopted first to have the greatest positive impact?
5. What are the tangible benefits to wood products producers for successful transition to lean manufacturing?
6. Are certain segments of the wood industry leaner than others, and is this a contributing factor to their relative resistance to overseas competition?

To answer these questions, a data-driven analytical methodology is more likely to be effective in gauging an effective transformation than subjective assessment schemes or anecdotal evidence so often cited in the literature. Our review of the lean literature led the research team to believe that no research has been conducted to quantitatively describe the relationships among

wood recovery, production, consumption, and inventory in terms of lean production for the wood products industry. The objective of this research was therefore to apply a statistical tool, factor analysis, to quantitatively develop a lean production metric, which we call a Lean Index, for the wood products industry. In this exploratory research effort, we set out to address the first question above, to establish an operational metric by which wood products companies can assess their level of leanness relative to similar wood products operations and other operations within their company.

STATEMENT OF PROBLEM

Although lean production was originally designed for the auto industry, it has been applied widely to other industrial areas such as aerospace (Murman et al. 2002), construction (Garnett et al. 1998), wood products (Shingo Prize News 2003), and many others. Lean can be an efficient means to improve manufacturing quality, minimize inventory and waste, and ensure continuous improvement (Womack and Jones 1996). Typically, lean production efforts include the following characteristics, or components (Askin and Goldberg 2002; Allen et al. 2001):

- 5S: sort, straight, scrub, standardize, self discipline;
- Pull System/Kanban: produce only the customer order through production control;
- Cellular/Flow Manufacturing: make the product batches as small as possible;
- Set up reduction (SMED): quick die change and machine set up;
- Total Productive Maintenance (TPM): include total effectiveness, total preventive maintenance, and total participation;
- Value Stream Mapping: a process for following a product's production path from beginning to end;
- Visual manufacturing: enable operators and managers to quickly distinguish normal and abnormal in the process;
- Team work: a competitive team that harmonizes among people.

Typical of the benefits attributed to lean production are those cited by Kotelnikov (2001):

- Reduction of waste by 80% (waste includes intellect, motion, overproduction, transportation, inventory, waiting, and defects);
- Reduction of inventory by 80%;
- Decrease in manufacturing cycle times by 50%;
- Reduction in labor by 50%;
- Increased capacity in facilities by 50%;
- Improved product quality by 50%;
- Higher profits;
- Higher system flexibility;
- Better cash flow;
- Just-in-time delivery.

However, it has been demonstrated that differential realization of benefits occurs when lean production techniques are implemented in industries other than the auto industry (Womack and Jones 1996) because every industry has its own economic situation and system of operations. In order to facilitate consistent evaluation of lean production efforts, many lean assessment tools have been developed and introduced by various research or consulting groups. The ultimate objective of these lean assessment tools has been to investigate, evaluate, and measure the current manufacturing situation against the "standard" lean characteristics, as well as assess lean implementation and continuous improvement during the lean implementation. One typical assessment tool measures leanness in nine different areas including inventory, the team approach, process, maintenance, plant layout and material handling, suppliers, set-up, quality, and production control and scheduling (Strategos 2003). A score is based on the answers to multiple questions in each area in an effort to describe leanness.

To answer many of the questions in typical lean assessment tools, it is necessary to collect information about a manufacturer. However, the data collection process may be difficult for the typical company to perform with assurance of data validity and non-bias. One assessment tool, the Lean Enterprise Self-Assessment Tool (LESAT) developed by LAI (Nightingale and Mize 2002), utilizes maturity matrices that mea-

sure 54 lean practices consisting of lean transformation/leadership, life cycle processes, and enabling infrastructure processes. Five maturity levels were defined from least capable (1) to world class (5) for each item. Other examples of lean assessment tools are the Supply Chain Assessment and Lean Evaluation System (SCALES) developed by K3 Business Technology Group (2002), and the Lean Assessment Screen Tool by Kumar and Thomas (2003). Finally, even the most widely accepted benchmark of lean competence, the Shingo Prize (2003) lists fifteen different measures in five different categories as the basis for lean measurement.

The existing lean assessment tools are based on questionnaires that explore different areas of a company's manufacturing practices. However, most surveys are subjective and require detailed knowledge of aspects of facility operation that may be hidden to the company's management. Therefore, depending on management's internal view of corporate actions and resulting impact, biased survey assessments may result, especially for a large facility. A data-driven analytical methodology may be more effective in stating the effectiveness of a lean transformation than these subjective assessment schemes (Wilson and Pearson 1995). However, no apparent research has been done to develop an objective, unbiased, quantitative approach to evaluate lean accomplishment, or to assist in determining the priority of lean implementation efforts. In particular, no specific standard definition for lean production, relative to wood products industries, exists (Ray 2003).

PRELIMINARY INVESTIGATION OF PROBLEM

In September 2003, our research team conducted an organizational meeting (see Michael et al. 2003) with twenty-eight industry participants to structure a lean production research project that would define possible metrics for lean production in the wood producing industries. In a brainstorming session, the industry partners produced a list of 54 management challenges and 81 possible determinants (metrics) of whether or not a company is lean. This high

number of issues and metrics indicated what we suspected—that management in the wood products industry really did not have a clear understanding of how to identify “leanness,” even though several of them claimed to have lean operations. Table 1 summarizes the responses obtained at the meeting; duplicate and similar responses were synthesized post-meeting to increase clarity of thought.

Participant responses were elicited in random fashion from a live, group interview, in an attempt to promote brainstorming and free-thinking; the ordering and pairing of challenges with associated metrics was done by the research team post-meeting. Many issues were named for which no corresponding metric was mentioned. For the purposes of this discussion, these particular issues, which are conceptually more complex, are omitted from Table 1. The table illustrates that from a management point of view, even the more straightforward management issues surrounding the concept of “lean” are complex; that metrics are sometimes confused with issues, and vice versa; and that given the number of different metrics cited, there is not a clear standard or prioritization of the various metrics associated with the production of wood products.

Therefore, it is posited that the concept and proof of lean do not at this time have unique standards of measurement specific to an industry under study, at least at the macro-process level (see Juran 1989). Nor is there any way to effectively measure the current state of “leanness” of any particular operation. Further, our in-plant work with many different manufacturers suggested that when it comes to lean, visual impressions may not accurately reflect true levels of resource utilization. Therefore, we sought to develop a way to quantitatively and objectively assess the true leanness of any wood products company. In the development of this model, we sought to develop a metric that would act as a single, simple, yet comprehensive measure that could adequately represent the dynamic complexities inherent in the widely differing wood products industry sectors. Hayes et al. (1988) provided a precedent for this approach. They

TABLE 1. Summary of lean research planning participant responses to management challenges and metrics of a lean production effort.

Management challenge	Metrics
Production Cost/Product Costing	Production/manhour Product cost/unit Overall Labor Cost Warranty costs
Production Time	Set-up time Throughput time
Inventory Control	Inventory turns Raw material inventory investment Inventory levels (Raw material, WIP, Finished)
Yield Maximization vs. Value Maximization	Yield Raw material cost Profit Scrap rates Overrun
Production Scheduling	Throughput Number of required sorts per schedule Production/demand ratio per product Run lengths
Employee Commitment & Involvement	Employee efficiency Safety performance Testing results Employee morale
Management Commitment/Training/Project Preparation	Cross-training %
Procurement of/ Return on Capital	Plant utilization Return on investment
Competitive Benchmarks	Market share vs. competition
Process Re-engineering Time/Cost	Time to implement
Pull Manufacturing	Order size Order variability
Managing Raw Material Lead Time	Lead time Cash flow
Space Utilization	Sales \$/sq.ft.
Overhead/Accounting/Documentation Costs	Overhead percentage of sales Service costs Logistics/transportation costs
Customer Satisfaction	On-time delivery On-spec delivery Sales volume Product quality Lead Time Price reduction history Profit margin
Supplier Relationships	Procurement cost

were able to combine multiple measures of productivity, which they labeled Total Factor Productivity (TFP). They defined TFP as a function of output of a product to the sum of the resource inputs necessary to produce that product. To apply TFP across a product line with different resource inputs, and to relate TFP to performance

of the firm, the authors used dollar quantities to standardize and represent the resource flows.

Because dollar quantities present problems of scale between operations of different types, and in different regions of the world, Total Factor Productivity seems to be a close, but not exactly perfect, measure of leanness for an industry in

which similar financial results can occur from widely different utilization of similar resources. For this reason, the research team sought to eliminate dollar quantities wherever possible and instead use physical quantity measures. If properly standardized, these quantity measures would provide non-biased equivalent comparisons. The methodology used in development of this new measure is detailed in the following section.

MODEL DEVELOPMENT

The research team sought to develop a methodology and resulting metric to objectively and quantitatively assess the “leanness” of any wood products operation. The general hypothesis formed was that for any common set of input variables and outcomes, an indicator metric could be modeled and calculated that would represent the current state of leanness for any wood products operation. The resulting metric would then constitute a standard by which all wood products companies could assess their current state of leanness, analyze the relative leanness of various areas of their operation, and prioritize improvement efforts.

Twelve wood products operations were visited and at each a schematic process input-output model was developed. From these models, common input and output variables were established. Preliminary screening of data was performed using principal component analysis, and insignificant variables (those whose variance was too small to help distinguish between members of the population) were eliminated from further modeling efforts. Table 2 shows those input, output, and inventory variables and their associated units of measure that were determined, through statistical significance of variables common to all twelve operations studied, to be essential components of a “macro-level” view of the leanness of an operation.

Most statistical modeling techniques (e.g., regression, ANOVA, etc.) are used to study the relationship between independent and dependent variables. However, in this research, the lean index (dependent variable) could not be quanti-

tatively measured or collected directly from the companies, because it did not exist. Rather, a technique was needed to derive the dependent metric directly from the independent variables (i.e., the macro-level inputs and outputs of each operation). In the process, the independent variables had to be screened and properly standardized to reflect their proper relative contribution to the resulting index. Zhang and Ray (1995) provided an excellent discussion on different multi-variable ranking techniques, and developed a methodology for using these ranked criteria to develop a product evaluation index for different particleboards in North America. Their “modified principal component technique” utilized theory from principal component analysis and factor analysis, and resulted in one composite index score for each particleboard, based on a data set containing data on twenty-five different product attributes.

Since the objective of this research was to describe leanness using the many and complex variables directly measured from manufacturers in a single, simple, scaled index metric, the objective became to develop a single quantitative descriptive factor from the entire set of response variables. Factor analysis is a statistical approach that describes the patterns of relationships among quantifiable variables, with the goal of identifying variables that cannot be directly measured (Pett et al. 2003). Afifi and Clark (1990) state “that the main purpose of factor analysis is to derive from the data easily interpretable common factors.” In the forest products literature, this technique has most commonly applied in the social sciences; for example, Bush and Sinclair (1991) used factor analysis to define different dimensions of competitive strategy in the hardwood industry. This research team recognized a similar problem with respect to measuring leanness; there is a lot of data to interpret, but no “easily interpretable” bottom-line metric to be measured as the dependent variable. Factor analysis was thus selected as the modeling technique of choice.

Factor analysis reduces the number of original, or response, variables to a smaller number of subsets, called “principal components.” By

identifying the principal components, the interrelationships between response variables (inputs, outputs, inventories) and principal components of the unknown variable (in this case, leanness) can be determined and analyzed. These interrelationships, commonly called *loadings*, are quantified as the correlation coefficients of each response variable to each principal component. To more efficiently model the system under study, a rule of thumb allows the modeler to exclude from further analysis all response variables that do not exhibit a loading of at least 0.40 with at least one of the principal components (e.g., see Pett et al. 2003). Also, based on the variance (eigenvalue) of each principal component, "factors" are extracted. Each factor with an eigenvalue over 1.0 is retained and utilized in a basic factor model where the response variables $X_{p \times 1}$ are assumed to be linearly dependent on factors $F_{m \times 1}$, as shown in Eq. (1).

$$X_{P \times 1} = \mu_{P \times 1} + L_{P \times m} F_{m \times 1} + \varepsilon_{P \times 1} \quad (1)$$

where

X is response (original) variable vector

μ is mean of X

L is loading matrix

F is the extracted factor matrix

ε is random error (specific factors)

P is number of observed variables

m is number of factors (usually $m < p$)

This process combines the intercorrelations among the remaining response variables and the factor loadings, resulting in factor score coefficients. Finally, these coefficients are linearly summarized into a "factor score," utilizing the coefficient of each response variable that corresponds to the factor to which that variable is most highly correlated, as demonstrated by its higher loading factor.

In the context of defining a metric for the assessment of leanness, this derived factor score, the metric hidden at the root of this research effort, came to be termed a "Lean Index" (LI). At this point, the research hypothesis was refined to state that the lean indices, generated for each company, could be used to measure their overall leanness, relative to the rest of the wood

products industry. Further, the lean indices as generated for each distinct operation within the company could be utilized to define lean improvement priorities.

DATA COLLECTION

Of the twelve wood products manufacturers visited, quantitative data sets were collected from nine. These nine companies included fifteen different operations as defined in the course of the study: three saw mills, four drying operations, four rough mills, two furniture assembly operations, one cabinet producer, and one pallet producer. Seven of the nine companies provided historic data (either a monthly average or end-of-month level) for each variable retained in the study, for a one-year period. One of the two remaining companies provided data for only nine months, and the final company could provide only one month's data; for this company, eleven additional data records were generated using Monte Carlo simulation, producing randomly generated numbers from a uniform distribution around the mean of each variable. In total, 102 observations were collected and used to build the factor analysis model.

Figure 1 illustrates the macro-level representation that was used to create data collection templates for each company participating in the study. The data collection templates were customized for each company through process flow-charting efforts. Company personnel filled in the resulting data collection templates. For most companies, this was a straightforward process, since the physical measures called for in the study usually already resided somewhere in their operational databases. The research team provided additional clarifications and unit conversion assistance in each case, and verified the data through follow-up interviews and validation of apparent outlier data points.

Data standardization

Prior to the process of model formulation, the collected data had to be standardized to eliminate bias due to the scale and operational differ-

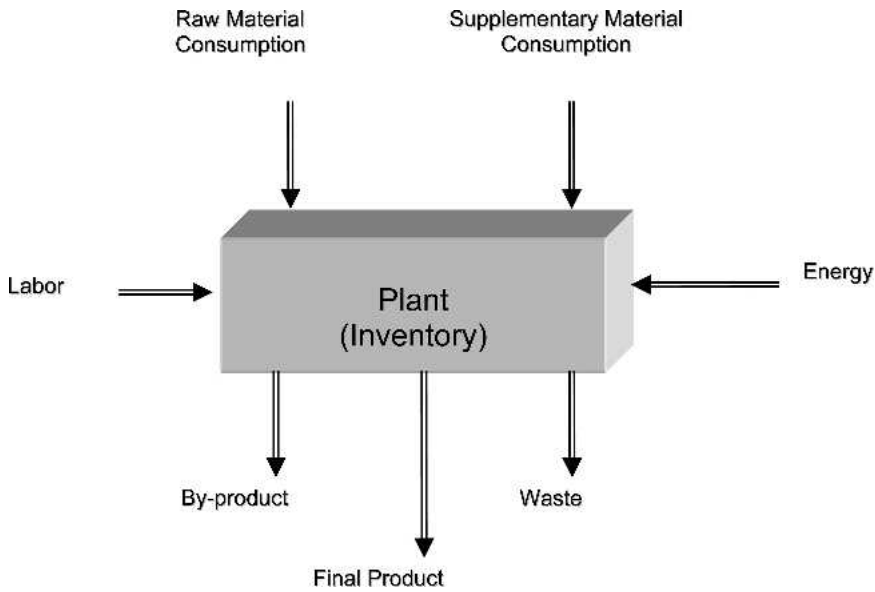


FIG. 1. Simplified graphical representation of a macro-level model of a typical hardwood products manufacturer.

ences of the companies in the study. Data standardization is a process of changing all data to an equal range to ensure consistency and comparability and to minimize variations in the analysis caused by differences in scale (Milligan and Cooper 1988). Typically, standardized variables are simply the variable divided by its sample standard deviation. However, since we were trying to achieve meaningful results from disparate data sets, a bit more complexity was required. Data standardization in this project was a three-step process:

1. Convert individual variables to a common unit of measure.
2. Transform all model variables into a function of a common variable that will minimize potential bias introduced by the difference in the sizes of the participant companies.
3. Normalize the transformed variable data for purposes of comparison.

Data standardization, Step 1.—Common variables measured with multiple unique units of measure were converted to a common, uniform unit. For example, energy usage is measured in kilowatts (electricity), BTU’s (wood fuel), and CCF (natural or propane gas). In this example, our modeling efforts converted and analyzed all energy units in kilowatts. Similarly, board footage is used to measure raw material consumption (e.g., logs or lumber), final products generation (e.g., lumber, dimension parts, furniture or cabinets), and inventories. Tonnage was used for the amount of by-product such as sawdust, mulch, or chips. The analysis units for Lean Index modeling as used in this project are shown in Table 2.

Data standardization, Step 2.—The operations of the nine manufacturers in this study varied in plant size, quantity of annual raw material consumption, and product generation. One vari-

TABLE 2. Variables, and their selected unit of standardization, collected for each distinct operation within each participating company.

Items	Input			Output		Inventory	
	Energy	Wood	Non-wood	Production	By-products	Inventory	Supplies
Unit	Kw/hr	bf/hr.	\$/hr.	bf/hr.	ton/hr.	bf/hr.	\$/hr.

able unit of measure all these operations had in common, regardless of their size or business, was "labor hours" (i.e., the number of man-hours required to make product). Thus, to make equivalent comparisons and to avoid statistical bias in the model, all values of each variable were standardized with respect to man-hours (labor hours). Equations (2) to (8) show the formulas used to make the conversions.

$$\text{Wood} = \frac{\text{total raw material}}{\text{total labor hours}} \quad (2)$$

$$\text{Production} = \frac{\text{total shipped products}}{\text{total labor hours}} \quad (3)$$

$$\text{Energy} = \frac{\text{total energy consumption}}{\text{total labor hours}} \quad (4)$$

$$\text{Nonwood} = \frac{\text{total cost of supplementary material}}{\text{total labor hours}} \quad (5)$$

$$\text{Inventory} = \frac{(\text{raw material inventory} + \text{WIP inventory} + \text{product inventory})}{\text{total labor hours}} \quad (6)$$

$$\text{By-Product} = \frac{\text{generated byproduct}}{\text{total labor hours}} \quad (7)$$

$$\text{Supplies} = \frac{\text{supply inventory}}{\text{total labor hours}} \quad (8)$$

In addition to the collected data listed in Table 2, three additional variables were identified during the research planning meeting as essential to characterizing the leanness of an operation: raw material inventory turnover, inventory turnover, and final product inventory turnover. Raw material inventory turnover is defined as the ratio of the raw material consumption to the raw material inventory (Eq. 9). Inventory turnover is the ratio of the quantity of sold products to the sum of product inventory and work-in-process inventory (Eq. 10). Final product inventory turnover is the ratio of the quantity of sold products to the final product inventory (Eq. 11).

$$\text{Raw_turnover} = \frac{\text{total raw material consumption}}{\text{raw material inventory}} \quad (9)$$

$$\text{Inventory_turnover} = \frac{\text{total shipped products}}{\text{WIP inventory} + \text{product inventory}} \quad (10)$$

$$\text{Product_turnover} = \frac{\text{total shipped product}}{\text{final product inventory}} \quad (11)$$

Data standardization, Step 3.—Once the model variables had all been converted and transformed, one data standardization step remained. The newly formed variables were again transformed, this time to standard scores, to normalize the data. This is a proven way of normalizing, proposed by several authors (Dubey and Jain 1980; Everitt 1980; Lorr 1983; Romesburg 1984; Sokal 1961; Spath 1980; and Williams et al. 1964). This procedure allows data from different operational processes, with different orders of magnitude, to be compared on an equivalent basis. Equation (12) is the formula for normalization.

$$Z_1 = (X - \bar{X})/s \quad (12)$$

where

Z_1 is the fully standardized response variable
 X is the original data value (from Step 2)
 \bar{X} is the sample mean
 s is the sample standard deviation

MODEL DETERMINATION

The entire 9-company, 10-variable data set was then processed using the SAS procedure PROC FACTOR (SAS Institute 2002), and the program's output was examined to determine the best model for the lean index.

RESULTS AND DISCUSSION

The resulting eigenvalues (Table 3) revealed that a 2-factor model would adequately represent the data, accounting for 82.18% of the total vari-

TABLE 3. SAS PROC FACTOR reduced correlation matrix eigenvalues of original, 9-company, 10-variable data set.

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	4.41826962	2.19279933	0.5465	0.5465
2	2.22547029	1.17086387	0.2753	0.8218
3	1.05460642	0.67752956	0.1305	0.9523
4	0.37707686	0.23697173	0.0466	0.9989
5	0.14010513	0.13007933	0.0173	1.0163
6	0.01002580	0.01768717	0.0012	1.0175
7	-0.00766137	0.00353795	-0.0009	1.0166
8	-0.01119933	0.02185330	-0.0014	1.0152
9	-0.03305263	0.05659746	-0.0041	1.0111
10	-0.08965009		-0.0111	1.0000
Total	8.08399071			

ance of the data. Table 3 also indicated that a 3-factor model was a borderline improvement, with the third factor exhibiting an eigenvalue of 1.05; subsequent modeling supported the decision to use the 2-factor model. However, the 2-factor model of Table 3 is over-specified; it can be seen in Table 4 that two of the response variables, Supplies and By-Products, can be excluded. Variable By-Products failed to pass the 0.40 rule of thumb for inclusion in either of the two factors. While variable Supplies barely passed this rule in Factor 2 (0.40196), the research team felt that the Supplies data were not reliable enough to include in the model considering the borderline level of significance.

With these two variables included in the

TABLE 4. Initial factor loadings summary of original, 9-company, 10-variable data set.

Variable	Factor1-production throughput	Factor2-production support
Production	0.94970	-0.09207
Inventory_turnover	0.82180	0.39561
Wood	0.81818	-0.23758
Product_turnover	0.77111	0.47089
Inventory	0.76153	-0.57528
By-products	-0.29248	-0.01382
Raw_turnover	-0.69611	0.45298
Energy	0.54773	0.80445
Non-wood	-0.28087	0.66126
Supplies	0.21913	0.40196
Variance Explained by Each	4.4182696	2.2254703
Factor Percentage (Total 82.2%)	54.7%	27.5%

model, the grouping of response variables to each factor according to their highest loading does not produce factor groupings that can be easily defined by the variables of which they consist. Therefore, it was determined to exclude Supplies and By-Products, and repeat the procedure with the remaining 8 variables; the results are shown in Tables 5 and 6.

The 8-variable model is more satisfactory for a variety of reasons. First, the percentage of the total variance explained by the 2-factor model increased to 85.9%. No variable exhibits a loading of lower than 0.7. Perhaps most importantly, the resulting groupings of response variables into factors according to their new loadings revealed a more interesting possible definition of the factors. That is, Factor 1 is now comprised of Production, Wood, Inventory, and the three Turnover variables. This suggested a grouping of production or flow-related variables; we thus labeled Factor 1 as "Production Throughput." Factor 2, comprised of Energy and Non-Wood, might similarly be labeled "Production Support." We can see from Table 6 that Production Throughput accounts for roughly twice as much (57.8%) of the total variance of "leanness" as Production Support (28.1%).

Once the variables have been grouped into factors through the loading analysis described above, it is necessary to compute weights, or "scores," for each variable relative to the dependent variable being defined if a comprehensive index is to be developed. Of the many possible ways to compute these weightings, SAS uses a

TABLE 5. SAS PROC FACTOR reduced correlation matrix eigenvalues of reduced, 9-company, 8-variable data set.

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	4.29302884	2.20863185	0.5780	0.5780
2	2.08439699	1.13558878	0.2807	0.8587
3	0.94880821	0.81473158	0.1278	0.9864
4	0.13407662	0.10173273	0.0181	1.0045
5	0.03234389	0.04323064	0.0044	1.0088
6	-.01088675	0.00665255	-0.0015	1.0074
7	-.01753930	0.01975366	-0.0024	1.0050
8	-.03729296		-0.0050	1.0000
Total	7.427			

Factors 1 and 2 will be retained by the NFACTOR criterion.

regression procedure to compute these factor score coefficients, which are used in linear fashion to combine the standardized x_i 's into factor scores. The resulting factor score model (Table 7), taking Production, Wood, Inventory, and the three Turnover coefficients from the Factor 1 column (due to their higher loading in Factor 1, Table 6), and Energy and Non-Wood coefficients from Factor 2 (higher loading in Factor 2, Table 6), is given in Eq. (13).

$$\begin{aligned}
 \text{Factor score} = & 0.133 * \text{Wood} \\
 & + 0.262 * \text{Production} \\
 & - 0.197 * \text{Inventory} \\
 & - 0.005 * \text{Raw_turnover} \\
 & + 0.256 * \text{Product_turnover} \\
 & + 0.130 * \text{Inventory_turnover} \\
 & - 0.363 * \text{Energy} \\
 & - 0.197 * \text{Non-wood} \quad (13)
 \end{aligned}$$

TABLE 6. Final factor loadings summary of reduced, 9-company, 8-variable data set.

Variable	Factor 1-production throughput	Factor 2-production support
Production	0.95634	-0.02854
Inventory_turnover	0.80624	0.40964
Wood	0.83225	-0.15449
Product_turnover	0.75492	0.46277
Inventory	0.77913	-0.53480
Raw_turnover	-0.70383	0.46656
Energy	0.52191	0.82810
Non-wood	-0.30179	0.69880
Variance Explained by Each		
Factor	4.2930288	2.0843970
Percentage		
(Total 85.9%)	57.8%	28.1%

The signs and values of the variable coefficients in the factor score model are quite interesting. Since the interpretation of the resultant score is "the higher, the better (leaner)," then increased production, product turnover, and inventory turnover all contribute to an operation being leaner, while increased inventory detracts from leanness. These results agree with common assumptions of lean production.

Raw material turnover, however, has only a slight impact on the final determination of leanness, although its loading of the principal components indicates that it contributes significantly to total variation. The interpretation of this result is that raw material turnover varies substantially across the industry, but with mixed results on the leanness of various operations. This could be quite significant in defining this aspect of lean production benchmarks in the wood products industry in that certain types of wood operations may find it beneficial to maintain large inventories of raw materials, possibly even at in-process

TABLE 7. Linear regression results of factor scoring (LI) model.

Standardized scoring coefficients		
Variable	Factor 1-production throughput	Factor 2-production support
Production	0.26155	0.12048
Inventory_turnover	0.13003	0.10682
Wood	0.13330	0.05287
Product_turnover	0.25611	0.10685
Inventory	-0.19774	0.57867
Raw_turnover	-0.00547	-0.06384
Energy	0.44149	-0.3634
Non-wood	0.11055	-0.19721

stages of production. For these operations this should not necessarily be construed to be an “un-lean” practice. The obvious example is a sawmill with a large log inventory or supply of contracted timber. However, it might also hold true for secondary operations that choose to retain large inventories of dry lumber, or components, so that they can respond rapidly to just-in-time order demands.

As increased wood consumption correlates to higher throughput per unit of time, we see the expected positive contribution of wood usage to the LI. However, usage of both energy and non-wood materials (the Production Support variables) detract significantly from the leanness of the operation. In fact, their combined coefficients have a negative impact on Lean Index roughly four times as great as the positive impact of wood consumption. This might suggest possibilities such as:

- Companies with energy-intensive operations might focus first on ways to reduce energy consumption in any process re-design or improvement efforts, rather than focusing primarily on process flow improvements;
- These same companies may benefit from outsourcing of energy intensive operations, notably drying operations;

- Companies dealing with non-wood component suppliers must ensure that these suppliers are as lean as possible and can deliver required components in “lean” quantities and schedules so as to not to waste the added value potential of that product feature.

Lean performance assessment

Next, the individual monthly data sets from each company were plugged into the resultant LI model (13) to produce macro-level LI's for each company. In order to improve the LI metric by giving it a “user-friendly” scale, another data manipulation was conducted to make sure that all factor scores became positive numbers, roughly between 0 and 12. The higher the LI, the more lean the company. Equation (14) shows the formula for lean index calculation.

$$\text{Lean Index} = \exp(1.5 + \text{Factor score}) \quad (14)$$

This particular manipulation may need to be revised as new data sets are added.

The results of the factor scoring analysis are shown in Fig. 2. Each grouping of dots represents monthly Lean Index metrics for each of the nine companies. The average Lean Index for

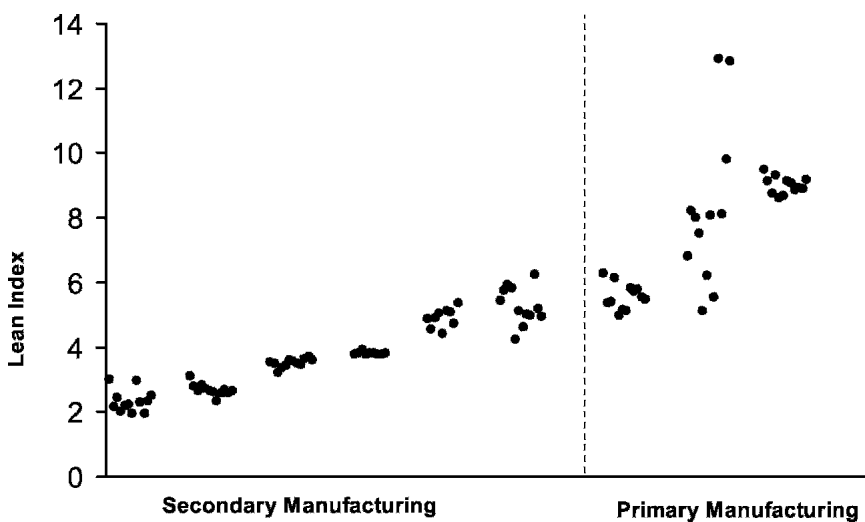


FIG. 2. Macro-level Lean Indices for nine wood products companies.

these nine companies is 5.07. Interestingly, Fig. 2 demonstrates that six of the companies, all secondary wood products operations, had lower LI's than the other three. These six secondary operations exhibit an average LI of 4.60, with a range from 2.33 to 5.27. The other three companies, all primary wood processors (lumber operations), exhibit an average LI of 6.06, with a range of 5.55 to 12.00. This suggests that based on the definitional standards of lean production developed in this study, primary operations are inherently leaner than secondary operations.

One lumber operation exhibited an unusually wide range of LI's for the year; this was a small sawmill that literally was on the verge of running out of logs several times due to wet weather during the year. At these times, the operation truly looked lean; the log yard was empty, logs were being loaded directly, just-in-time, onto the log-deck from the incoming log trucks, and finished lumber was being bundled, loaded, and shipped as fast as it could be graded. The management agreed that they were indeed running as lean as they could be, at these times; but they were not comfortable operating in this mode.

As demonstrated, the Lean Index model can be used to compare leanness of one company to another. Perhaps more importantly, the model can also be used to describe leanness of each distinct operation within a company, at any given stage during lean implementation, and therefore can be applied to help establish resource allocation priorities. Two case studies, of a primary manufacturer and a secondary manufacturer, follow.

Case study 1: Sawmill.—Company A is a medium-size sawmill producing veneer logs and kiln-dried lumber. The company has been in business for more than 200 years and owns a large holding of timberland with a wide variety in hardwood species. The operation was grouped into five distinct operations: log yard, saw mill, green lumber yard, kiln-drying operation, and dried lumber warehouse. Figure 3 schematically represents the flow of resources through each operation within the company.

The monthly data for year 2002 provide an overall lean index for Company A of 5.56. The

lean indices of the five operations range from 3.23 to 10.44 (as shown in Fig. 3). The kiln-drying operation is the least lean operation with a lean index of 3.23, and the lumber warehouse is the leanest operation with a lean index of 10.44. In this case, the LI metrics suggest that the priority of lean implementation, or improvement, efforts should be: 1) kiln-drying operation, 2) log yard, 3) lumber yard, 4) sawmill, and 5) lumber warehouse.

Case study 2. Furniture company.—Company B is a furniture company producing customized wooden library furniture. Product demand is seasonal with a peak in the summer and a relatively constant and substantially lower demand the rest of the year. The data collected for this company were for the nine month off-season demand period. The operational components are identified as lumber warehouse, dimension mill, composite panel warehouse, panel mill, assembly and finishing station, and packaging and product warehouse (Fig. 4). The overall lean index of Company B is 3.80 and the lean indices of each operation range from 2.91 to 7.46 (as shown in Fig. 4). The assembly and finishing center has the lowest lean index of 2.91, while the composite panel warehouse is the leanest operation with a lean index of 7.46. The lean indices of the individual operations suggest the priority for lean implementation should be: 1) assembly and finishing, 2) packaging and warehouse, 3) dimension and machining, 4) lumber warehouse, 5) panel mill and machining, and 6) composite panel warehouse.

These case studies also hint at another potential use of the LI model. Any company benchmarked with the LI, and considering potential changes to an operation, could estimate the impact on the response variables caused by the potential change. They could then plug these estimates into the LI model, and observe how that particular process "improvement" changes the overall and operation-by-operation assessment of leanness. This would allow the company to determine whether that proposed change would have the desired and expected impact, from a viewpoint of the "leanness" of the operation. The research team experimented with this form

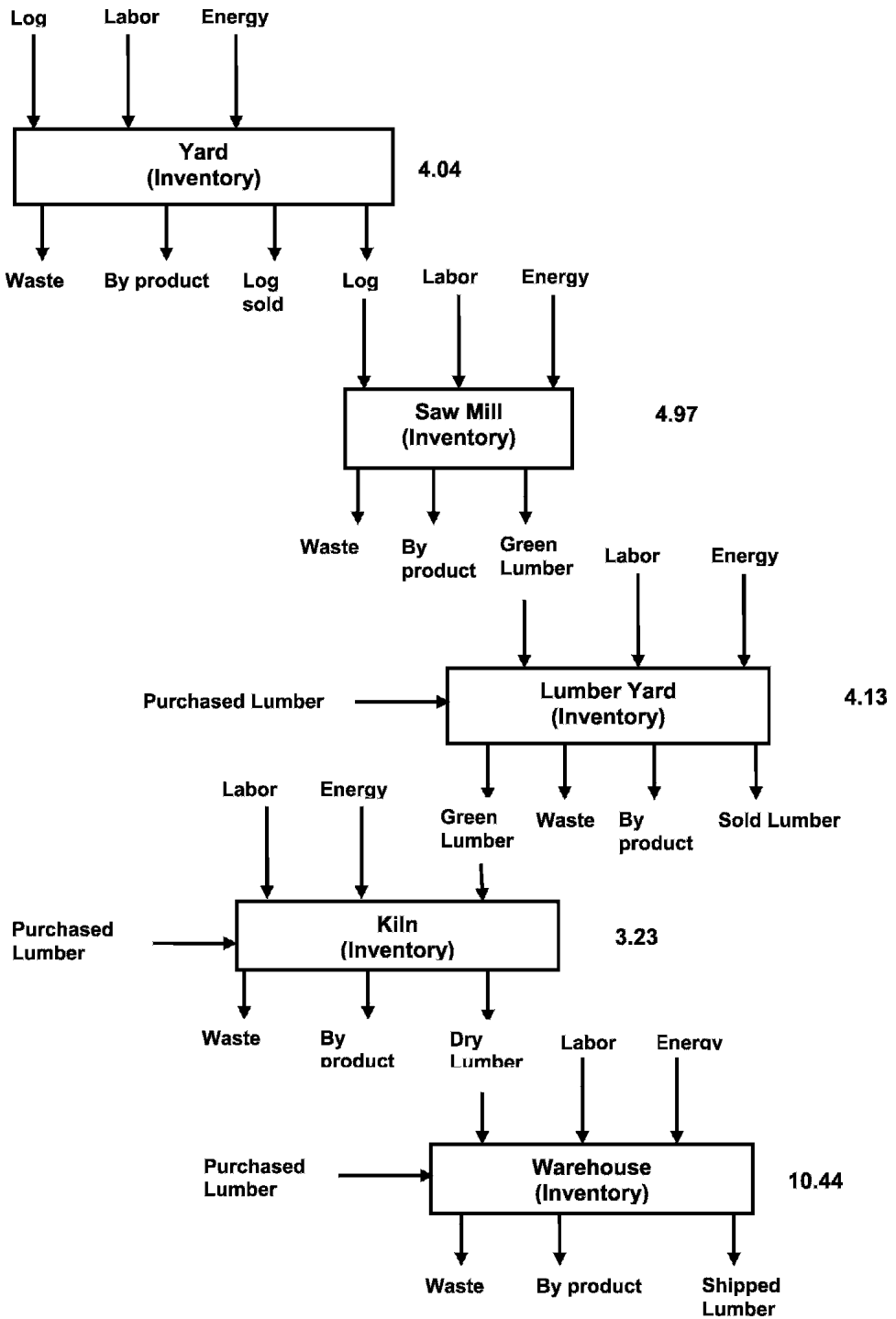


FIG. 3. Resource flow and lean indices by operation for Company A, a sawmill.

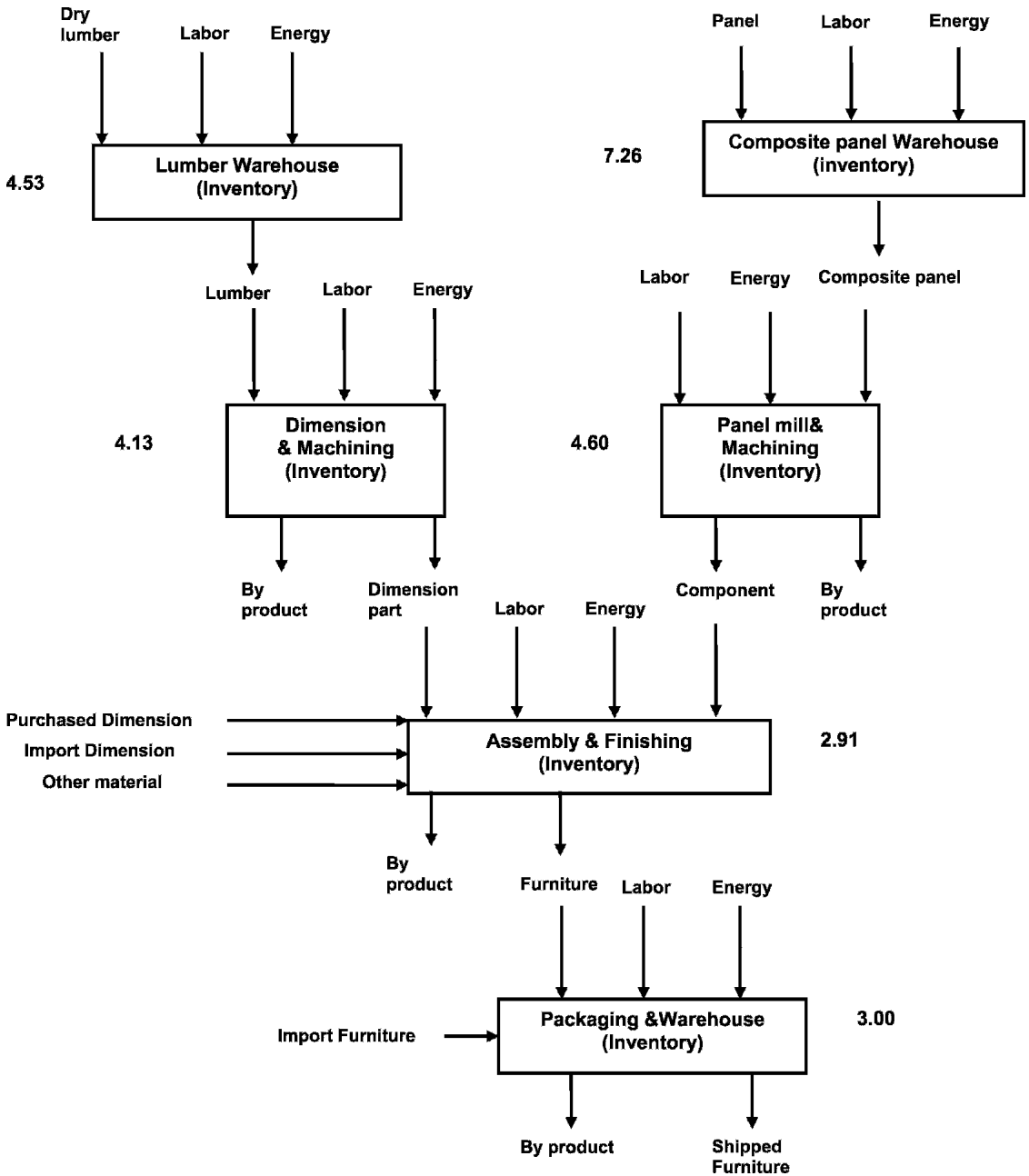


FIG. 4. Resource flow and lean indices by operation for Company B, a furniture company.

of “lean simulation,” and discovered that the factor analysis methodology employed to derive the lean indices allows the lean metrics to change dynamically throughout the operation, even though only one operation is changed. This

is due to the fact that the total variance, each response variable’s contribution to that variance, and accordingly, the eigenvalues of each factor, are altered by any change, addition, or deletion of the original data.

Limitations

As exploratory research and observation, this study has application limitations. As a work to help define “lean production” and assess its implementation in the wood products industry, the data set (nine companies) is not robust enough to make generalizations for the entire industry as to the potential benefit of lean production for its various sectors. Therefore, the resulting Lean Index coefficients and scores reported in this paper could be biased by specific variable differences in the companies in the study, and these coefficients and scores can only be made more reliable and repeatable through the addition of additional data to the model.

In addition, the Lean Index metric itself must be validated in some way, either by independent generation of corroborating Lean Indices from additional data collection and/or simulation efforts, proven correlation of the LI to some accepted bottom-line productivity measure across an entire group of subject companies, or by case studies that report successful improvement efforts as prioritized by the LI assessment.

CONCLUSIONS

This study demonstrates that the statistical methodology of factor analysis can be used to develop a quantitative definition and assessment of the concept of “leanness” for any wood products company. Accordingly, the Lean Index, as developed, makes a unique contribution to the field of lean production research and technology transfer; in addition to the well-known techniques of kaizen, just-in-time production, set-up reduction, total productive maintenance, “5S”, and mistake-proofing, companies in the wood products industry now have at their disposal an objective, unbiased way to evaluate their lean implementation efforts and the performance of their operational processes under both “current” and “improved” conditions. The Lean Index technique appears to be superior to traditional, subjective, questionnaire-based assessments, in that the subjectivity and bias of company participants are removed from the analysis. Also,

the Lean Index gives the company a way to assess the leanness of individual operations within their company and to prioritize their lean improvement efforts and commitment of resources.

Based on the standards of lean production developed in this study, primary wood products operations appear inherently leaner than secondary wood products operations. This hypothesis will continue to be tested as future data sets are obtained. If the trend continues to hold true, the separation of primary and secondary wood operations into two separate models is suggested. However, one recent data set, representing twelve months of operation in a secondary wood company after making some “lean” improvements, pushed the company into the range of LI’s reached by the primary manufacturers. This suggests that “lean is lean” regardless of what type of operation is being studied.

Development of the Lean Index model also moves us closer to a clear and logical definition of lean production for the wood products industry. Through the process of variable reduction and factor extraction, the model quantitatively defines leanness in terms of only two factors, which can be characterized as “Production Throughput” and “Production Support.” Recognizing the conceptual difference in the two factors, lean improvement efforts may be categorized accordingly; the traditional lean techniques mentioned above may be used to change the *Production Throughput* components of the operation, prioritized by the Lean Index metric; while *Production Support* components may be targeted with perhaps more appropriate engineering analyses. For example, the fact that energy usage has the largest coefficient in the Lean Index model indicates that engineering improvements that reduce energy consumption may be the most significant contribution to lean production efforts in the wood products industry.

In previous research of lean production techniques, the operations studied typically were assembly operations where the primary “energy” provided was by the labor component of the operation; thus, in prior studies, lean techniques focused on reducing the consumption of labor, not energy *per se*. It might be concluded that for

any industry (such as wood products), where physical energy-intensive conversion of a primary raw material is a significant consumer of resources, a standard definition of “lean production” must include a measure of the efficiency of energy consumption and/or product conversion.

Finally, we must emphasize that the results of this effort lead us to believe that “classical” lean techniques and metrics, while certainly holding the potential to improve any wood products operation, may hold potential pitfalls and limitations as well. Large inventories, large batch sizes, and long lead times are “classical” non-lean symptoms; since however, it is probably not always practical or profitable to hold small inventories of logs, lumber, or components, run smaller cutting bills, dry significantly smaller volumes of wood, or to increase wood drying rates by orders of magnitude, the Lean Index model described in this paper indicates that an optimal lean implementation methodology for wood industry operations should include, along with the “classical” lean techniques, tactics geared toward better utilization of *all* resources consumed in the production of the products.

REFERENCES

- AFFIFI, A. A., AND V. CLARK. 1990. Computer-aided multivariate analysis. Van Nostrand Reinhold, New York, NY. 505 pp.
- ALLEN, J., C. ROBINSON, AND D. STEWART. 2001. Lean Manufacturing: A Plant Floor Guide. Total Systems Development, Inc. Dearborn, MI. 495 pp.
- ASKIN, R. G., AND J. B. GOLDBERG. 2002. Design and analysis of lean production systems. John Wiley and Sons, Inc. New York, NY. 533 pp.
- BUSH, R. J., AND S. A. SINCLAIR. 1991. A multivariate model and analysis of competitive strategy in the U.S. hardwood lumber industry. *Forest Science* 37(2):481–499.
- DUBES, R., AND A. K. JAIN. 1980. Clustering methodologies in exploratory data analysis. *Advances in Computers* 19: 113–228.
- EVERITT, B. S. 1980. Cluster analysis. 2nd ed. Heinemann, London.
- GAGNON, M., AND J. MICHAEL. 2003. Employee strategic alignment at a wood manufacturer: An exploratory analysis using lean manufacturing. *Forest Prod. J.* 53(10):24–29.
- GARNETT, N., D. T. JONES, AND S. MURRAY. 1998. Strategic application of lean thinking. Proceedings IGLC. 1998.
- HAYES, R. H., S. C. WHEELWRIGHT, AND K. B. CLARK. 1988. Dynamic manufacturing—Creating the learning organization. The Free Press, A Division of MacMillan, Inc., New York, NY. 429 pp.
- JURAN, J. M. 1989. Juran on leadership for quality—An executive handbook. Chapter 7—Operational quality management. The Free Press, A Division of MacMillan, Inc., New York, NY. 376 pp.
- K3 BUSINESS TECHNOLOGY GROUP. 2002. <http://www.manufacturingtalk.com/news/ktp/ktp109.html>
- KENNY, M. AND R. FLORIDA. 1993. Beyond mass production. Oxford University Press. Oxford, UK and New York, NY. 410 pp.
- KESSER, W. C. 1999. Implementing lean thinking. *Information. Knowledge. System Management* Vol. 1:99–103.
- KOTELNIKOV, V. 2001. Lean production consulting web site. http://www.1000ventures.com/presentations/production_systems.html.
- KUMAR AND THOMAS. 2003. User manual for lean assessment screening tool. University of Toledo, Toledo, OH.
- LORR, M. 1983. Cluster analysis for the social sciences. Jossey Bass, San Francisco, CA.
- MICHAEL, J., C. D. RAY, AND X. ZUO. 2003. Lean production research meeting. <http://woodpro.cas.psu.edu/ResearchMeetingfinal.pdf>
- MILLIGAN, G. W., AND M. C. COOPER. 1988. A study of standardization of variables in cluster analysis. *J. Classification* 1988(5):181–204.
- MURMAN, E., T. ALLEN, K. BOZDOGAN, J. CUTCHER-GERSHENFELD, D. NIGHTINGALE, E. REBENTISCH, T. SHIELDS, F. STAHL, M. WALTON, J. WARMKESSEL, S. WEISS, AND S. WIDNALL. 2002. Lean enterprise value. Palgrave, New York, NY. 344 pp.
- NELSON, R. R. 1991. Why do firms differ, and how does it matter? *Strat. Mgmt. J.* 12:61–74.
- NIGHTINGALE, D. J., AND J. H. MIZE. 2002. Development of a lean enterprise transformation maturity model. *Information, Knowledge, System Management* Vol. 3:15–30.
- OHNO, T. 1988. Toyota production system: Beyond large-scale production. Foreword by Norman Bodek. Productivity Press, Portland, OR. 143 pp.
- OLIAN, J., C. DURHAM, A. KRISTOFF, K. BROWN, R. PIERCE, AND L. KUNDER. 1998. Designing management training and development for competitive advantage: lessons from the best. *Human Resources Planning* Pp. 20–31.
- PENN STATE MANAGEMENT DEVELOPMENT. 2002. The Lean Enterprise Assessment Tool. The Pennsylvania State University, University Park, PA.
- PETT, M. A. N. R. LACKEY, AND J. J. SULLIVAN. 2003. Making sense of factor analysis: the use of factor analysis for instrument development in health care research. SAGE Publications, Thousand Oaks, CA. 348 pp.
- RAY, C. D. 2003. Lean Manufacturing for the Wood Products Industry. Penn State WoodPro TechNote 2003-1. <http://woodpro.cas.psu.edu/TechNotes.htm>
- ROMESBURG, H. C. 1984. Cluster analysis for researchers. Lifetime Learning Publications, Belmont, CA.

- SAS INSTITUTE. 2002. SAS user's guide. Cary, NC.
- SHINGO PRIZE. 2003. <http://www.shingoprize.org/BusPrize/recipients/current/Merillat%20Atkins%20Profile.doc>
- SOKAL, R. R. 1961. Distance as a measure of taxonomic similarity. *System Zoology* 10:70–79.
- SPATH, H. 1980. Cluster analysis algorithms. John Wiley and Sons, New York, NY.
- STRATEGOS. 2003. <http://www.strategosinc.com/assessment.htm>.
- WILLIAMS, W. T., M. B. DALE, AND P. MAC NAUGHTON-SMITH. 1964. An objective method of weighting in similarity analysis. *Nature* 201:426.
- WILSON, P., AND R. D. PEARSON. 1995. Performance-based assessments. ASQC Quality Press, Milwaukee, WI.
- WOMACK, J. P., AND D. T. JONES. 1996. Lean thinking: Banish waste and create wealth in your corporation. Simon and Schuster, New York, NY.
- , ———, AND D. ROOS. 1990. The machine that changed world. 1st HarperPerennial ed. HarperPerennial, New York, NY. 323 pp.
- ZHANG, J., AND C. D. RAY. 1995. Modified multivariate evaluation techniques for industry-wide product surveys. Proc. Third International Applied Statistics in Industry Conference, Dallas, TX. ACG Press, Wichita, KS.